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A spatial epidemiological approach on well-being in urban slums – Evidence from Dhaka, Bangladesh

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However, in general, I try to get my mind relaxed and rested while running by not thinking about anything. I run to cool down my nerves that get heated up while writing.

Haruki Murakami

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Abstract

Urban health is of global concern because the majority of the world's population lives in urban areas, mainly in the global south. Although mental health problems (e.g., depression) in developing countries are highly prevalent, such issues are not yet adequately addressed in the rapidly urbanising megacities of these countries, where a growing number of residents live in slums. Little is known about the spectrum and burden of mental disease in urban slums. Using a spatial-epidemiological approach, this thesis identifies factors that contribute to mental well-being in the slums of Dhaka, the capital of Bangladesh, which currently accommodates an estimated population of more than 14 million, including 3.4 million slum dwellers. The baseline data from a cohort study conducted in early 2009 in nine slums of Dhaka were used. Data were collected from 1,938 adults (≥15 years). The WHO-5 Well-being Index was used as a measure of self-rated mental well-being. It was found that mental well-being was significantly associated with various factors such as selected features of the natural environment, flood non-affectedness, sanitation, and housing quality, sufficiency and durability. Further associations with population density, job satisfaction, and income generation were identified while adjusting for individual factors such as age, gender, diseases, health knowledge, and migration. Spatial clusters of poor and good mental well-being among different population groups were detected and point to severe health disparities both within and between the slums. Diverse neighbourhood conditions affected mental well-being differently from personal and household level characteristics. Given that mental health conditions could elevate the risk for physical diseases and contribute to injuries, this thesis may provide crucial information for developing better health care and disease prevention programmes in Dhaka's slums and other comparable settings.

Zusammenfassung

Urbane Gesundheit ist von globalem Interesse, da schon jetzt die Mehrheit der Menschen in Städten wohnt und dies zunehmend in Entwicklungsländern. Obwohl mentale Gesundheitsprobleme (z.B. Depressionen) in Entwicklungsländern stark verbreitet sind, wurden diese für die rasant anwachsenden Städte dieser Länder bisher nicht zufriedenstellend untersucht. Mit einem räumlich-epidemiologischen Ansatz werden in der vorliegenden Dissertation Faktoren identifiziert, welche das mentale Wohlbefinden der Slumbewohner Dhakas beeinflussen. Hierfür wurden Baseline Daten einer Kohortenstudie verwendet, welche Anfang 2009 in neun Slums in Dhaka durchgeführt wurde. Es wurden Daten von 1.938 Erwachsenen (≥15 Jahre) erhoben. Der WHO-5 Well-being Index wurde als Instrument zur Selbsteinschätzung des mentalen Wohlbefindens verwendet. Mentales Wohlbefinden war signifikant mit verschiedenen Faktoren der natürlichen Umwelt, der Sicherheit vor Überflutungen, sanitären Verhältnissen, sowie mit qualitativ hochwertiger, zufriedenstellender und beständiger Behausung assoziiert. Weitere mentale Gesundheitsassoziationen wurden in Bezug auf Bevölkerungsdichte, Zufriedenheit mit der Arbeitsstelle und mit der Einkommensgenerierung identifiziert, während für individuelle Faktoren wie Alter, Geschlecht, Krankheiten, Gesundheitswissen und Migrationshintergrund angepasst wurde. Räumliche Konzentrationen von gutem und schlechtem mentalem Wohlbefinden wurden festgestellt, welche auf massive Gesundheitsungleichheiten innerhalb der Slums hindeuten. Verschiedene Nachbarschaftskontexte wirken sich zudem in anderer Weise auf das Wohlbefinden aus als persönliche und Haushaltscharakteristika. In der Annahme, dass mentale Gesundheitsprobleme das Risiko physischer Krankheiten sowie die Unfallgefahr erhöhen, liefert diese Dissertation wichtige Informationen, um sowohl eine bessere Krankheitsversorgung als auch sinnvolle Krankheitspräventionsprogramme für die Slums von Dhaka und vergleichbarer Gebiete zu entwickeln.

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Chapter I: Introduction

1 Mental health in an urbanising world

Mental health conditions are a growing concern, as they increasingly contribute to the global burden of disease (WHO 2004). Neuropsychiatric disorders (including depression, alcohol and substance abuse, and psychoses) add to the so-called disability-adjusted life-years (DALYs) i.e., the sum of years lived with disability and years of life lost. This contribution is projected to increase worldwide from 13.5% in 2005 to 14.4% in 2030 (Mathers and Loncar 2006; Prince et al. 2007).

The World Health Organisation (WHO) defines mental health[1] as "*…a state of well-being in which the individual realizes his or her own abilities, can cope with the normal stresses of life, can work productively and fruitfully, and is able to make a contribution to his or her community.*" (WHO 2005: 2). In the developing world, however, mental health may become especially threatened due to increased urbanisation rates and inadequate low-income housing, overcrowding, crime, environmental pollution, loss of social connections, food insecurity, poverty, and limited access to basic services within cities (Harpham 1994; Patel and Kleinman 2003; Harpham 2009; Lund et al. 2010). Additionally, globalisation and lifestyle changes affect diet and exercise patterns and increasingly contribute to poor population health, including increased mental illness, in the megacities of developing countries (WHO 2001; National Research Council 2003; Harpham 2009).

In low-income countries, depression has become almost as prevalent as malaria (3.2% versus 4% of the total disease burden) (WHO 2010), and this number is projected to further increase to ~5% in 2030 (cf. Table I-1) (Mathers and Loncar 2006). Hence, developing countries are facing a double burden of both communicable (e.g., malaria) and non-communicable diseases (e.g., mental health conditions). Indeed, mental disorders may further elevate the risk for communicable and non-communicable diseases and contribute

[1] The terms "mental health" and "well-being" will be used interchangeable throughout this thesis.

to intentional and unintentional injuries (Prince et al. 2007) i.e., group I, II, and III diseases according to the global burden of disease framework[2], respectively (Pinheiro et al. 2010).

Table I-1: Ten leading contributors to years lived with disability and life lost (DALYs).

Low-income countries, projection for 2030		
Rank	**Disease or injury**	**Percent of total DALYs**
1	HIV/AIDS	14.6
2	Perinatal conditions	5.8
3	Unipolar depressive disorders	4.7
4	Road traffic accidents	4.6
5	Ischaemic heart disease	4.5
6	Lower respiratory infections	4.4
7	Diarrhoeal diseases	2.8
8	Cerebrovascular disease	2.8
9	Cataracts	2.8
10	Malaria	2.5

DALY: Disability-adjusted life year, Source: Mathers and Loncar (2006)

After the “urban turn” in 2008, the majority of the world’s population is now living in cities. Over 9% of the global urban population in 2009 were living in 21 megacities each with more than 10 million inhabitants (UN 2010). The number of megacities is expected to increase to 29 by 2025, at which point they are expected to account for 10% of the world’s urban population. Whereas in 1975, there were only 3 megacities worldwide, Mexico City, New York City, and Tokyo, by 2025, Asia alone will have 15, Latin America 6, Africa and Europe 3, and the US 2. Thus, mega-urbanisation is primarily occurring in Asia, more specifically, in China (5 megacities), India (3), Japan (2), Pakistan (2), and Indonesia, the Philippines, and Bangladesh (1 megacity each) (UN 2010).

[2] The Global Burden of Disease (GBD) framework is a joint approach of the World Health Organisation (WHO), the World Bank, and the Harvard School of Public Health with the main objective to generate an internationally comparable set of estimates of mortality and morbidity. Within this framework, the Disability-Adjusted Life Year (DALY) was developed, to summarise the global disease burden. The GBD classification system defines

The huge urban growth rates in most developing countries' megacities are due to either migration from rural areas or to natural increases in the urban population, with both driving factors being equally important (National Research Council 2003). Megacities comprise high population concentrations, strong development dynamics, infrastructure, economic power, and administrative and political functions and are therefore considered to be nodal points in today's globalised world (Kraas 2007). They are the economic motor of a country or region for the generation of financial resources, which are necessary for improved living standards. Megacities provide many advantages for citizens, including improved health care and social services as well as better income possibilities and education as compared to rural areas (National Research Council 2003).

However, rapidly urbanising megacities, especially those of developing countries, are confronted by a number of serious challenges, which include loss of governability, increased informal economic activities (Kraas 2007), and an elevated double burden of disease, including mental ill-health (Harpham 2009). Furthermore, environmental hazards induced by a changing climate are equally important, as they either push villagers to move to the cities to find alternative income sources (Hunter 2005) or affect a large part of the urban poor within the megacities themselves (cf. Braun and Aßheuer 2011). Hazards range from increased risks of extreme weather events to infectious disease and a heightened sea level, leading to the salinisation of land and water sources (WHO 1990; McMichael 2000; WHO 2009). In any case, it is the urban poor who are particularly vulnerable to economic, social, and political crises as well as environmental hazards and disasters (National Research Council 2003) and poor mental health (Lund et al. 2010; WHO 2010). In addition, the urban poor population is largely incapable of accessing health and social services provided in the cities because of a lack of financial resources (National Research Council 2003).

These megacity challenges in developing countries underlie the overarching goals for this dissertation: (i) to assess the factors that describe the mental health of poor populations

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three broad disease cause groups: Group I, II, and III causes including communicable, non-communicable diseases, and injuries, respectively (Pinheiro et al. 2010).

residing in a megacity's slums; (ii) to investigate the spatial variability of mental health status for different population groups in slums; and (iii) to identify whether the local neighbourhood affects the mental health of slum dwellers. These findings may contribute to a more sophisticated knowledge of the relationship between health and the socio-physical environment in comparable megacity slums.

2 Mental well-being in urban slums

The rapid urban growth in developing countries is most often combined with informality, illegality, unplanned settlements, and a lack of administrative planning, leading to spatial segregation and the development of slums. According to Sclar and Northridge (2003), slums are the spatial manifestation of urban poverty, social exclusion, and inappropriate government policies. Hence, slums and squatter settlements[3] have to be considered crucial components in the megacities of developing countries and cannot be neglected. Within informal settlements, processes similar to those occurring in formally planned neighbourhoods are taking place, however, with a much greater emphasis on environmental and infrastructural deprivation, poverty, crime, and self-regulation as well as an increased double burden of disease faced by a population that has been widely neglected by the public sector (National Research Council 2003; Riley et al. 2007; Harpham 2009; Sverdlik 2011).

UN-HABITAT (2003: 12) defines a slum household as one or a group of individuals living under the same roof in an urban area and lacking one or more of the following five amenities: (1) durable housing, (2) sufficient living area, (3) access to improved water, (4) access to improved sanitation facilities, and (5) secure tenure. However, in many slums of the developing world, all of these amenities are simultaneously lacking, thereby inducing known negative impacts on the physical and psychological well-being of urban slum residents (Sclar et al. 2005). Considering the global phenomena of poverty and slum formation, in the year 2000, the United Nations launched the Millennium Development

[3] Squatter settlements are usually unauthorised settlements on public land (cf. CUS et al. 2006). In the following, the terms slum, squatter- or informal settlement are used interchangeable and no differentiation is made.

Goals (MDGs), which focus on health and education (cf. Table I-2) (UN 2009). However, although closely linked to many of the MDGs, mental health is not explicitly mentioned (Patel 2007).

For instance, there is substantial evidence that poverty is related to poor mental health (cf. Patel and Kleinman 2003; Howell and Howell 2008; Harpham 2009; Lund et al. 2010). Furthermore, people with mental disorders must cope with the burden of health care costs and are prone to the loss of employment opportunities. Provision of mental health resources to those in need would help to provide a safety net and offer opportunities for individuals to no longer exist in poverty (MDG 1) (Patel 2007).

Moreover, children in developing countries are often not able to either enrol in schools or complete primary education (MDG 2) due to their various types of learning disabilities (Prince et al. 2007; Patel et al. 2008). The prevalence of depression and anxiety is often found to be significantly higher in women as compared to men (MDG 3) (Harpham 2009). Additionally, depression during pregnancy is one of the most common health problems among women (MDG 5), and depression during motherhood is associated with low birth weight and other complications that may lead to infant mortality (MDG 4) (Prince et al. 2007; Patel et al. 2008). There is also evidence of co-morbidity between HIV/AIDS (MDG 6) and mental health. For example, Patel (2007) identified studies in which individuals with alcohol use disorders (a mental health problem) are at greater risk for contracting HIV/AIDS and that people with HIV/AIDS are more likely to have mental disorders, which, in turn, may affect their overall health condition.

Table I-2: The UN Millennium Development Goals (MDGs).

Goal 1	Eradicate extreme poverty and hunger
Goal 2	Achieve universal primary education
Goal 3	Promote gender equality and empower women
Goal 4	Reduce child mortality
Goal 5	Improve maternal health
Goal 6	Combat HIV/AIDS, malaria and other diseases
Goal 7	Ensure environmental sustainability
Goal 8	Develop a global partnership for development

Source: UN (2009)

Since the launch of the MDGs, a significant improvement in the lives of at least 100 million slum dwellers has already been achieved (one target of MDG 7). Thus, the proportion of the population living in slums in the developing world has declined from 39% in the year 2000 to an estimated 33% in 2010 (UN-HABITAT 2010). Despite these improvements, the absolute number of slum dwellers is still rising, as the urban population in the developing world has increased rapidly, i.e., from 767 million slum dwellers in 2000 to 828 million in 2010 (cf. Figure I-1 for a global distribution of slum dwellers in 2005). Based on these trends, the world's slum population is expected to reach 889 million by 2020 (ibid).

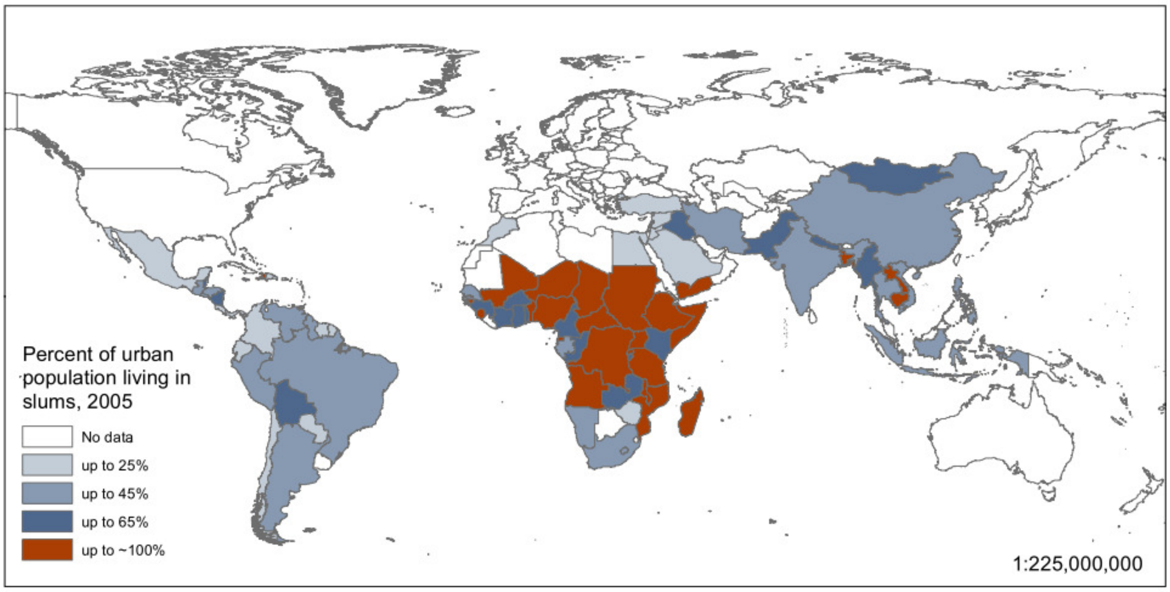

Figure I-1: Urban population living in slums 2005. Source: Author's design based on data from UN-HABITAT (2011).

To date, little is known about the burden of disease in the urban slums of the developing world (Riley et al. 2007), and research on the mental health status of slum residents is lacking (Izutsu et al. 2006). The need to target slum dwellers who encounter mental health problems is further underlined by the "United Nations Convention on the Rights of Persons with Disabilities", which advocates the inclusion of disability issues into strategies for sustainable development (WHO 2010). The lack of data concerning the spectrum of diseases and disabilities in slums, including mental health conditions, further hampers the efficient allocation of health care initiatives and the provision of appropriate disease prevention services (Riley et al. 2007). Given that mental disorders elevate the risk for group I, II, and III diseases (Prince et al. 2007), understanding disease burden and HDFs in slums is urgently needed.

3 Megacity Dhaka

Dhaka, the capital of Bangladesh, is the 9th largest city worldwide, with 14 million inhabitants (UN 2010). It is also one of the fastest growing megacities in the world, and the UN predicts that with approximately 21 million inhabitants by 2025, it will become the 5th largest city in the world (ibid).

The mega-urban region of Dhaka expanded nearly three-fold during a 16-year period from approximately 162 km² in 1990 to nearly 440 km² in 2006 (Griffiths et al. 2010). Prime agricultural areas and wetlands, generally known to provide important ecosystem goods and services (ESS), were therefore lost. This rapid megacity development, coupled with an inadequate urban management system, further promotes excessive overcrowding, traffic congestion, environmental pollution, food insecurity, energy shortage, and an increasing informal economic sector (IGS 2010; Siddiqui et al. 2004; Islam 2005).

Poverty, lack of job opportunities and natural disasters in the rural area trigger the population push towards the city (Burkart et al. 2008). In Dhaka, 300,000 new rural-to-urban migrants arrive every year (Afsar 2000; World Bank 2007) and initially concentrate in slum settlements (CUS et al. 2006; Islam 2005). This leads to an increased proportion of the urban population living in slums (e.g., from 20% in 1996 to 37% in 2005), with Dhaka now hosting about 3.4 million slum dwellers (CUS et al. 2006).

Poverty, poor housing, high population densities and inadequate living conditions combined with poor environmental conditions weaken the health of slum-dwellers and thus intensify the double burden of disease in Dhaka (CUS et al. 2006). Furthermore, the formal health sectors normally treat slum dwellers at the end-stage complications of chronic illnesses, and thus, slum dwellers sometimes need to address medical issues at a tremendous cost to their personal socio-economic resources (Riley et al. 2007).

The Bangladesh National Mental Health Survey in 2003-2005 revealed that approximately 16% of the adult population was suffering from mental disorders. As only very few patients report to the government facilities (WHO 2006) and assuming that slum dwellers are neglected by the public sector (Riley et al. 2007), it is likely that this number is biased. There is no specific mental health authority in Bangladesh, mental disorders are not covered in social security schemes, and only 4% of the training for medical doctors is devoted to mental health (WHO 2006). As stated by the WHO - Assessment Instrument for

Mental Health Systems (AIMS) report in 2006, data on the burden of mental diseases in Bangladesh is lacking, and information is insufficient. Furthermore, they state that only a small percentage of all health publications in the country were concerned with mental health (ibid).

4 Objectives and structure of the thesis

Taking Dhaka as an example, this thesis has three overarching goals, that are (i) to assess the factors that describe the mental health of poor populations residing in Dhaka's megacity slums; (ii) to investigate the spatial variability of mental health status for different population groups in slums; and (iii) to identify whether the local neighbourhood affects the mental health of slum dwellers.

Urban health has only recently emerged as a research discipline (Vlahov and Galea 2003), and the state of the art of this discipline shall be provided in Chapter II. This Chapter is written in the style of a review paper, which will be submitted to a peer-reviewed journal. The subsequent Chapter III focuses on the state of the art from a spatial epidemiological perspective, as this Chapter will introduce some of the technical aspects used in that research domain and is taken from the book Chapter "Spatial Epidemiological Applications in Public Health Research: Examples from the Megacity of Dhaka" by Gruebner et al. (2011a). Chapter IV examines the data, which was gathered by an extensive epidemiological survey in the slums of Dhaka in 2009. It further introduces the study region of Dhaka and provides some basic statistics on the survey data which will be used throughout this thesis. Chapters V to VIII are taken from individual research papers that are or will be published in international peer-reviewed journals.

Considering the first research goal of this dissertation, Chapter V reports on how HDFs in slums are identified and the findings obtained with this information. In reference to the second research goal, Chapter VI focuses on each slum separately and provides information on the spatial distribution as well as the spatial associations of HDFs and mental well-being. The last research goal is explored in Chapter VII.

This doctoral dissertation presents the methodology, results, and discussion sections of the individual research papers in Chapters V-VII along with the respective studies. In Chapter VIII, a synthesis of the reported findings concerning mental health in slums will be presented and advantages as well as limitations of the general approach will be provided.

Finally, an outlook for further studies within this research field will be given. The 7 Chapters are as follows:

Chapter II: Gruebner, O., Khan, M., Krämer, A., & Hostert, P. (in preparation). **Urban mental health in developing countries - a review.**

Chapter III: Gruebner, O., Khan, M.M.H., & Hostert, P. (2011). **Spatial Epidemiological Applications in Public Health Research: Examples from the Megacity of Dhaka**. In Krämer, A., Khan, M.H. & Kraas, F. (Eds.), Health in Megacities and Urban Areas (pp. 243-261). Physica-Verlag HD.

Chapter IV: Research area and data

Chapter V: Gruebner, O., Khan, M.M., Lautenbach, S., Müller, D., Krämer, A., Lakes, T., & Hostert, P. (submitted). **Mental health in the slums of Dhaka – a geo-epidemiological study**. BMC Public Health.

Chapter VI: Gruebner, O., Khan, M.M., Lautenbach, S., Müller, D., Krämer, A., Lakes, T., & Hostert, P. (2011). **A spatial epidemiological analysis of self-rated mental health in the slums of Dhaka**. International Journal of Health Geographics, 10, 36.

Chapter VII: Gruebner, O., Khan, M.M., Lautenbach, S., Müller, D., Krämer, A., Lakes, T., & Hostert, P. (in preparation). **Putting mental health into spatial context – a neighbourhood study in the slums of Dhaka**

Chapter VIII: Synthesis and outlook

Two appendices supplement this thesis:

Appendix A: The WHO (five) Well-being Index (1989 version)

Appendix B: Supplementary material for Chapter VI - Local cluster maps

5 The authors' contributions to the individual Chapters

Chapter II: I designed the paper, conducted the literature review and wrote the manuscript. M. Mobarak H. Khan critically revised the manuscript. Patrick Hostert and Alexander Krämer obtained the grant, designed the overall framework, critically revised the manuscript, and advised me throughout the research process.

Chapter III: I designed the paper and drafted the manuscript. M. Mobarak H. Khan helped to draft and critically revised the manuscript. Patrick Hostert obtained the grant, designed the overall framework and coordination, and helped to draft the manuscript. All authors read and approved the final manuscript.

Chapter IV: I designed the paper, performed statistical analysis, helped to design the cohort study, and wrote the manuscript. M Mobarak H Khan designed the cohort study and helped interpret the findings. Alexander Krämer and Patrick Hostert obtained the grant, designed the overall framework and coordination, and advised me in the whole research process. The cohort study was conducted jointly by M Mobarak H Khan and myself.

Chapters V to VII: I designed the papers, performed statistical analyses and drafted each manuscript. M Mobarak H Khan guided the statistical analyses and helped interpret the findings. Sven Lautenbach and Daniel Müller participated in the design of the papers and guided the statistical analyses and interpretation. Alexander Krämer and Patrick Hostert obtained the grant, designed the overall framework and coordination, helped to draft the manuscripts, and advised me in the whole research process. Tobia Lakes helped in designing and critically revising the manuscripts. All authors read and approved the final manuscripts.

Chapter VIII: The section "advantages and limitations" was taken from the above-mentioned research papers (Chapters V-VII). I designed the Chapter and wrote the manuscript.

Chapter II:
Urban mental health in developing countries – a review

Is the poor health of people living in deprived areas due to their own characteristics or behaviours or to features of the local environment? (Macintyre and Ellaway 2003: 24)

In recent decades, a number of studies have been published considering the relationships among social and environmental factors and urban population health. However, most evidence for these studies is derived from cities in developed countries. As living conditions and social and cultural aspects differ greatly between megacities in developing and developed countries, the evidence base is lacking important information. Mental health issues in particular, especially those of the urban poor, have not been adequately studied thus far in the context of urban health in developing countries.

This Chapter seeks to summarise key work in the field of urban health, placing emphasis on mental health of urban poor populations in developing countries. A literature review was performed using the Pubmed Central, Biomed Central, and ScienceDirect databases to identify eligible review papers on this topic. We particularly focused on review articles, as these provide a broader view of these issues. The keywords "mental" or "well-being" were combined with "slum", "neighbourhood" or "developing countries" and used to identify papers published in English within the last 10 years (June 5th 2001 to June 5th 2011). We further cross-checked the references of all identified manuscripts and performed a manual literature research on mental health of urban poor populations.

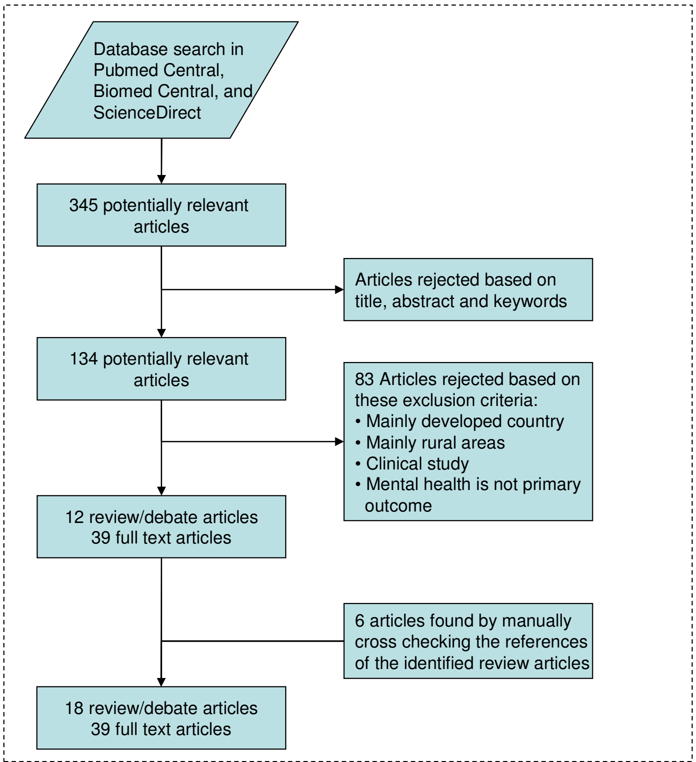

Figure II-1: Selection criteria for relevant manuscripts. Please note that we primarily focused on review/debate papers here and give only some examples from the identified full-text articles in this manuscript.

1 Mental health in urban areas of developing countries

Through our literature review, we identified 57 papers (cf. Figure II-1) that mainly examined mental health or well-being in urban areas mostly in developing countries. Thirty-nine of these were full-text research articles, and 12 were review articles. Through manually cross-checking the references of the review papers, 6 additional review articles were found. In the following section, we focus exclusively on review articles, as these provide a larger overview of the topic. Full-text papers are only used to provide further examples as needed in the text. See Table II-1 and II-2 for an overview of the identified review articles.

In their review, Caracci and Mezzich identify the four most frequently cited approaches to urban health up to 2001 (Caracci and Mezzich 2001). The first of these is the urban health penalty approach, which concentrates on the disadvantages of unhealthy environments in inner cities. Second, the urban sprawl approach focuses on urban growth and its effects on population health. For example, urban growth was often found to be associated with obesity, sedentary lifestyle and social isolation. Third, the urban health advantage approach focuses on the benefits of urban population regarding health care and social services due to proximity and better accessibility in comparison to rural areas. To date, another approach is widely found in the literature. This fourth method focuses on urban living conditions that are shaped through various contexts. This approach facilitates the modelling of urban population health (including mental health) as a function of individual factors being affected by the social and physical neighbourhood environment.

Table II-1: Review articles identified with a keyword search in Pubmed Central, Biomed Central, and ScienceDirect databases.

	Author (year)	Research goal	Main findings/conclusions
1	Caracci and Mezzich (2001)	To highlight the main themes of a vast body of literature on the subject of culturally mediated aspects of urban mental health and a culturally attuned delivery of mental health in urban areas.	Understanding the impact of cultural factors on urban mental health is necessary for a successful approach to mental health in cities.
2	Van Kamp et al. (2003)	To review the main (types of) concepts of liveability, environmental quality, quality of life and sustainability and to present examples of underlying conceptual models	A multidisciplinary conceptual framework of environmental quality and quality of life that goes beyond the disciplinary differences found in the current literature is needed if the field is to advance.
3	Vijayakumar et al. (2005)	To present a selective review of the socio-demographic, clinical,	In some developing countries, being female, living in a rural area, and holding religious beliefs

		and environmental / situational risk factors for suicide in developing countries	that sanction suicide may be of more relevance to suicide risk than these factors are in developed countries. Conversely, being single or having a history of mental illness may be of less relevance. Risk factors that appear to be universal include youth or old age, low socio-economic standing, substance use, and previous suicide attempts.
4	Patel (2007)	To provide an overview of mental health and alcohol use in developing countries	Mental disorders are common and pose a significant burden on the health of developing nations. Although the overall use of alcohol at the population level is relatively low, the consumption of alcohol is heavily gendered and is characterised by a high proportion of hazardous drinking among men. Hazardous drinking is associated with depressive and anxiety disorders as well as suicide and domestic violence.
5	Riley et al. (2007)	Urban slum dwellers comprise a neglected population that has become a major reservoir for a wide spectrum of health conditions that the formal health sector must deal with	Continued neglect of the ever-expanding urban slum populations in the world could inevitably lead to greater expenditure and diversion of health care resources to the management of end-stage complications of diseases that are preventable.
6	Egan et al. (2008)	To review literature reviews on the health associations of psychosocial risk factors in community settings	Favourable psychosocial environments go hand-in-hand with better health. Future research should seek to improve this evidence base with more longitudinal analyses (and intervention evaluations) of the effects of apparently under-researched psychosocial factors, such as control and participation within communities.
7	Howell and Howell (2008)	To synthesise the findings of 111 independent samples from 54 economically developing countries that examined the relationship between economic status and subjective well-being (SWB)	The average economic status-SWB effect size was strongest among low-income developing economies and among samples with the least education. The relationship was weakest among high-income developing economies and highly educated samples.
8	Wood and Giles-Corti (2008)	To explore beneath other aspects whether there is a place for social capital in the psychology of place	Social capital is not necessarily defined by, or confined to, geographically bordered communities. The link between physical environments, social capital and health supports efforts to include infrastructure and policy measures in interventions to improve social capital. Community infrastructure (such as a local libraries, schools or child health centres) or public amenities (such as parks with playgrounds or recreation centres) have inherent functional roles, but also serve as powerful conduits for social interaction and creating networks of support.
9	Barton (2009)	To summarise the evidence for the relationship between the	While personal factors are critical in determining health, the urban environment exacerbates or

		planning of settlements and health using a particular model based on eco-system and health determinants theories.	mitigates health and well-being outcomes. Access to green, natural environments and local social networks is a factor in mental well-being. The wider sub-regional pattern of housing, economic development, land use and transportation is a determinant of social exclusion and therefore health inequalities.
10	Chopra (2009)	To examine on the relationship between workplace environment and psychiatric morbidity	Common Mental Disorders (CMDs) have a negative impact on workplace productivity and adverse workplace environments are associated with a higher prevalence of CMDs. There are stark differences in workplace environment and standards in the developing world. In the current era of globalisation, greater attention is required to address the imbalance between workplace standards in the developed and developing worlds.
11	Harpham (2009)	To review the state of knowledge about urban health and the current priorities for research and action	The need to study urban health in a multilevel and multi-sectoral way is highlighted and priorities for research are identified. Concepts such as the double burden of ill-health and the urban health penalty approach are re-visited. Finally, a call for a shift from “vulnerability” to “resilience” is presented.
12	Lund et al. (2010)	To examine the high burden posed by common mental disorders (CMD) and the relationship between poverty and CMD in low- and middle-income countries (LMIC)	The relatively consistent association between CMD and a variety of poverty dimensions in LMIC serves to strengthen the case for the inclusion of mental health on the agenda of development agencies and in international targets, such as the MDGs.

Caracci and Mezzich (2001) further identify three main types of literature assessing urban mental health: (1) urban versus rural, (2) comparisons between cities, and (3) urbanisation and mental health. The authors stated that while the first two types often produce contradictory results or are difficult to generalise to other cities, studies focusing on the features of urbanisation and mental health are more informative. By studying discrete spatial units (neighbourhoods including communities), specific characteristics in the local environments that are associated with particular physical and mental health problems can be identified. Despite the context-specific nature, which makes it difficult to compare with other studies, this model allows for the establishment of a more focused and potentially successful plan for public health interventions (Caracci and Mezzich 2001).

Van Kamp et al. (2003) state that no generally accepted conceptual framework linking well-being and urban environmental quality has been developed, and Macintyre et al. (2002) also underline the need for an adequate conceptualisation, operationalisation, and measurement of “place effects” on health. Gee and Payne-Sturges (2004) and Galea et al. (2005b) were among the first to present conceptual frameworks for integrating psychosocial and environmental issues and urban population health, respectively. These frameworks shall be briefly introduced in the following section.

In their multidisciplinary framework, Gee and Payne-Sturges (2004) suggest that psychosocial stress may be the vulnerability factor that links social conditions with environmental hazards. They argue that psychosocial stress can cause acute and chronic changes in the functioning of body systems and also lead directly to illness. They also argue that residential segregation leads to differential experiences of community stress, exposure to pollutants, and access to community resources. They draw on the exposure-disease paradigm, a model demonstrating how environmental toxicants might cause disease. Furthermore, they propose that vulnerability increases or decreases the resistance to absorption and/or effects from toxicants. In their view, community or individual stress is one type of susceptibility factor (Gee and Payne-Sturges 2004).

The conceptual framework of Galea et al. (2005b) exclusively considers the health of urban populations. This model proposes that human activities and environmental conditions may be associated with factors that shape population health, such as economic development and social attitudes. The core concept underlying this framework is that the social and physical environments that define the urban context are shaped by municipal factors, such as government and civil society, and that national and global trends set the context in which local factors operate. The framework assumes that the urban environment in its broadest sense (physical, social, economic, and political) affects all strata of residents, either directly or indirectly. In order to consider all of these factors and the ways in which they affect the physical and mental health of urban populations, this conceptual framework proposes mechanisms through which these variables may influence the conditions that are the primary determinants of urban health. This leads to the conclusion that in order to understand urban health, it is important to shift the focus of inquiry away from disease outcomes towards urban exposures, namely, the characteristics of the urban context that influence health and well-being in cities. Furthermore, research on urban health must acknowledge the complexity of this field. This complexity itself can cause or exacerbate problems where a response to one part of a problem can precipitate an accident or disastrous unintended consequences (Perrow 1999). Approaches that recognise the importance of studying interactions at multiple levels are thus a useful tool in the study of urban health (Diez-Roux 2000; Vlahov and Galea 2003; Galea et al. 2005b).

Table II-2: Selected manuscripts identified through a manual literature research.

	Author (year)	Research goal	Main findings/conclusions
1	Macintyre et al. (2002)	To highlight what they consider to be a lack of adequate conceptualisation, operationalisation and measurement of "place effects"	The distinction between "composition" and "context" may be more apparent than real, and features of both material infrastructure and collective social functioning may influence health. The authors suggest using a framework of universal human needs as a basis for thinking about how places may influence health and recommend the testing of hypotheses concerning specific chains of causation that might link place of residence with health outcomes.
2	Gee and Payne-Sturges (2004)	To present a multidisciplinary framework integrating psychosocial stress that is suggested to be the vulnerability factor that links social conditions with environmental hazards	Psychosocial stress can lead to acute and chronic changes in the functioning of body systems (e.g., immune functions) and also lead directly to illness. They argue that residential segregation leads to differential experiences of community stress, exposure to pollutants, and access to community resources. When not counterbalanced by resources, stressors may lead to heightened vulnerability to environmental hazards.
3	Galea et al. (2005b)	To present a conceptual framework for studying how urban living affects population health	The framework rests on the assumption that urban populations are defined by size, density, diversity, and complexity and that health in urban populations is a function of living conditions that are in turn shaped by municipal determinants and global and national trends. The framework builds on previous urban health research and incorporates multiple determinants at different levels. It is intended to serve as a model to guide public health research and intervention.
4	Galea and Vlahov (2005)	To review the empirical research assessing urban living's impact on population health and our rationale for considering the study of urban health as a distinct field of inquiry	The key factors affecting health in cities can be considered within three broad themes: the physical environment, social environment, and access to health and social services.
5	Diez-Roux and Mair (2010)	To summarise key work in the area of neighbourhood health effects with a particular focus on chronic disease outcomes (specifically obesity and related risk factors) and mental health	Empirical work is classified into two main areas: studies that use census proxies and studies that directly measure neighbourhood attributes using a variety of approaches.

		(specifically depression and depressive symptoms)	The complexity of the topic is such that a combination of strategies will be necessary to understand the myriad of ways in which neighbourhood environments (together with other environments such as work, family, or school) may affect health and to determine the most promising interventions or policies for improving health.
6	Sverdlik (2011)	To review the literature on health in the informal settlements (and "slums") that now house a substantial proportion of the urban population in Africa, Asia and Latin America	The concluding section examines emerging risks such as non-communicable diseases and those associated with climate change. The authors note how more gender- and age-sensitive strategies can help address the large inequalities in health between those in informal settlements and other urban residents. With greater attention focused on the multi-faceted needs of low-income communities, governments can create interventions to ensure that urban centres fulfil their enormous potential for health.

In their review, Diez-Roux and Mair (2010) also provide evidence that features of neighbourhoods or residential environments may affect public health and contribute to social and race/ethnic inequalities in health. While summarising key work with a focus on chronic diseases and mental health, they identify four trends that are provided below.

1.1 Multilevel

The first trend identified by Diez-Roux and Mair (2010) states that purely individual-based explanations of the causes of ill-health are insufficient. They report that it is important to consider not only the characteristics of individuals but also the features of groups or contexts in which the individuals are living. Thus, neighbourhoods (residential areas) constitute the contexts in which socio-physical environments determine the physical and mental health of local residents. Therefore, recognising individual characteristics (endogenous) to be separate from the socio-physical environmental characteristics (exogenous) in a multilevel approach is becoming state of the art. This paradigm is supported by many authors researching urban health and the environment, albeit most of the studies are conducted in the developed world (Macintyre and Ellaway 2003; De Silva et al. 2005; Harpham 2009; Diez-Roux and Mair 2010). For example, when observing differences in health between places, those differences could be due to variations in the kinds of people living in these places (a compositional explanation) or to the differences between the places (a contextual explanation) (Macintyre and Ellaway 2003). In the context of a developing country, Subramanian et al. (2006) investigated the contributions of gender, caste, and standard of living to inequalities in mortality in India. The authors conducted a multilevel cross-sectional analysis of individual mortality using the 1998-1999 Indian National Family Health Survey data for ~530.000 individuals from 26 states. Substantially different mortality rates were observed between the lowest and highest standard-of-living quintiles across all age groups. Substantial caste differentials were observed at the beginning and end stages of life. Area variations in mortality are partially a result of the compositional effects of household standard of living and caste. The authors conclude that the mortality burden, across the life span in India, falls disproportionately on economically disadvantaged and lower-caste groups. Residual state-level (contextual) variations in mortality suggest an underlying ecology to the mortality divide in India.

Although initially there was some debate on the conceptualisation of context and composition, as some argue that this is an oversimplification, the concept of context and composition facilitates identifying the aetiology of poor or improved mental health in people to be separated from the health damaging or promoting factors of the environment. As such, the concept may convince policy makers to apply health interventions that focus not only on neighbourhood improvements but also on individual-based improvements or vice versa (Kawachi and Berkman 2003). However, there are also several fallacies related to the use of contextual and compositional variables, for example, the ecological and atomistic fallacies. The ecological fallacy is the incorrect inference that relationships observed at an aggregated level (e.g., between the percentage of migrants in a neighbourhood and the education level) will be observed in the same direction and magnitude at an individual level (e.g., the likelihood of migrants having only low education levels). Macintyre and Ellaway (2003) emphasise the importance of distinguishing between the inappropriate use of aggregated data as a proxy for individual level data (the ecological fallacy) with an ecological perspective, i.e., the analysis of socio-physical environmental associations with the health of individuals or populations. As the counterpart of the ecological fallacy, the atomistic fallacy is the incorrect inference of ecological associations from individual level data, for example, assuming that because all residents in a neighbourhood have high education levels, residents within this neighbourhood will only be non-migrants (Diez-Roux 2003; Macintyre and Ellaway 2003).

1.2 Race/ethnicity and social exclusion

A second trend identified by Diez-Roux and Mair (2010) is the increased focus on the origins of social inequalities as well as race/ethnic disparities in health. Gee and Payne-Sturges (2004) argue that racial/ethnical groups occupy different residential areas, which leads to environmental health disparities. Residence is therefore strongly linked to social position and ethnicity, rendering neighbourhood characteristics as important mental HDFs (e.g., inadequate health care, reduced access to social capital, or poor environmental quality) (Gee and Payne-Sturges 2004; Diez-Roux and Mair 2010).

1.3 Multi-sector

A third trend has been the persuasion of scientists and practitioners that measures for disease prevention must acknowledge the health effects of policies, which are not originally meant to improve health but that could have important consequences for public health (Diez-Roux and Mair 2010), e.g. access to labour and housing markets, urban planning, education policies, or policies for food security and food safety. It is obvious that the public health sector alone is not capable of reducing the physical and mental health problems of the poor population in developing countries. Government departments should communicate and coordinate their activities in a complementary fashion (Harpham 2009) and include NGO activities with their programs. For example, slum upgrading measures that target the sewage system could be combined with an intervention in health education, ensuring that illiterate residents also understand and make use of the new system. One example utilising this paradigm is the Healthy City initiative introduced by the WHO, which encourages consideration of health impacts by all city sectors, such as transport, industry and tourism (WHO 1995). However, implementation of this program has not been very fruitful, especially in developing countries, due to low political commitment (Harpham 2009).

1.4 New set of methods

Diez-Roux and Mair (2010) identified a fourth trend, the increased availability of methods to study neighbourhood health effects, such as multilevel analysis, geo-processing and geo-spatial modelling within GIS and spatial statistics available with spatial epidemiological approaches. The authors state that defining relevant spatial contexts is a crucial step but also includes several difficulties. One difficulty is that the spatial context relevant to a particular outcome may not be commonly thought of as a “neighbourhood” by the residents. Furthermore, social capital is not necessarily defined by geographically bordered neighbourhoods (Wood and Giles-Corti 2008). Another difficulty that Diez-Roux and Mair (2010) indentified is that spatial contexts other than residential, such as workplace contexts, may also be relevant. Another important issue they raise is the need to consider not only local areas or neighbourhoods that affect population health but also how the broader spatial context within which neighbourhoods are situated may add to or modify the effects of local areas (Diez-Roux and Mair 2010).

2 Mental health measures

The reviewed papers showed that various tools were used to assess common mental disorders (CMD) as a whole, such as the General Health Questionnaire (GHQ) (including a mixture of short and full versions), the Self-Reporting Questionnaire (SRQ-20) and the Revised Clinical Interview Schedule (CIS-R). Other screening tools were used to assess depression, such as the Edinburgh Postnatal Depression Scale (EPDS), Beck Depression Inventory (BDI) and the Centre for Epidemiologic Studies-Depression scale (CES-D). Structured diagnostic tools were used, such as the Composite International Diagnostic Interview (CIDI) to detect depressive or anxiety disorders according to DSM-IV, ICD-10 or DSM III-R criteria. Several studies used clinical interviews frequently as a second-stage assessment (Lund et al. 2010). Other studies used subjective well-being as a construct for mental health status (Howell and Howell 2008).

3 A conceptual framework for urban mental health in developing countries

3.1 The urban human-social system and mental health

Cities are embedded within global, national, and regional trends and dynamics and are therefore dependent on the major cultural, economic, and political frame in which they are situated. However, we sought to review the urban context exclusively, being well aware that this context may be overlapped by higher level determinants that are not considered here. We provide a conceptual framework that is depicted in Figure II-2. Furthermore, Gruebner et al. (2011b) provide a table (cf. Table II-3) that complements the framework and provides relevant urban environments at different levels.

Socio-economic environment

Galea et al. (2005b), for example, stress the central role of markets in determining the health of urban populations, as markets allocate crucial elements of a citizen's life, such as housing, food, employment opportunities, medical care, and transportation. Barton (2009) states that, particularly for poorer and less mobile groups, the allocation of available and affordable housing becomes a crucial part of spatial city planning. The structure of the housing market may force vulnerable residents to concentrate in less desirable neighbourhoods, thereby supporting patterns of increased deprivation and of spatial and social segregation with negative impacts on mental health (Gee and Payne-Sturges 2004).

In contrast to cities in high-income countries, rapidly growing megacities of developing countries are characterised by the dominance of informal sector markets (Harpham 2009; Gruebner et al. 2011b). The informal economy[4] may be defined as those of self-employment, workers with no registration, and owners of family business with fewer than 5 employees (ILO 2002; Harpham 2009). Although informal economic activities substantially contribute to the urban economy (Nwaka 2005; Heinonen 2008), the informal economy is often associated with low income and low occupational safety, as well as with legal and social insecurity, unfavourable working conditions due to pollutants, greater injury risk, discrimination, and exploitation (Barten et al. 2008).

Chopra (2009) reviewed two key models for the relationship between stress factors at work and mental health: the first being the demand-control model and the second being the effort-reward model. The first model recognises the level of demands that a job places on

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[4] More precisely, "*The term 'informal economy' refers to all economic activities by workers and economic units that are – in law or in practice – not covered or insufficiently covered by formal arrangements. Their activities are not included in the law, which means that they are operating outside the formal reach of the law; or they are not covered in practice, which means that – although they are operating within the formal reach of the law, the law is not applied or not enforced; or the law discourages compliance because it is inappropriate, burdensome, or imposes excessive costs*." (ILO 2002: 25/53).

the employee and the level of control that the employee is able to bear. Job-strain arises when the level of demand is high and the control level is low and is associated with common mental disorders and other health problems, including heart disease. The second model that they reviewed focuses on the effort an employee puts into his or her work and the reward the employee receives, including financial rewards, esteem, and prospects of promotion or job security. Not surprisingly, psychological stress arises when the rewards do not match the efforts invested. Moreover, due to missing safety nets and a lack of social security in developing countries, people need to continue to work despite having physical or mental problems (Chopra 2009).

Apart from the workplace, neighbourhood income inequality (the relative distribution of income within a neighbourhood) is thought to have substantial psychosocial impact on public health independent of individual socio-economic status (SES) (Fournoy and Yen 2004; Galea et al. 2007; Ompad et al. 2007; Harpham 2009; Diez-Roux and Mair 2010). Hence, where one lives becomes important as the place of residence is situated within a particular social milieu that can have considerable effects on health in terms of exposure, access to care, or social stress (Ompad et al. 2007).

Social environment

Harpham (2009) defines the urban social environment through interactions between people. As such, it includes negative interactions (violence, feeling insecure) as well as positive interactions (social capital). For example, high social capital in a neighbourhood is associated with behaviour that produces social supports and safety nets. Supporting behaviour in the neighbourhood may buffer the effects of life events on mental health. Furthermore, neighbourhoods with high levels of social capital are better able to establish and maintain educational, health and housing resources and are associated with better mental health outcomes (McKenzie and Harpham 2006). Egan et al. (2008), as well as Diez-Roux and Mair (2010), provided further evidence for mental health associations with social support and social capital. Those included measures such as the size of the social network, availability of supportive people, emotional support, collective efficacy, trust, social control and cohesion, reciprocity, participation, and community involvement. Furthermore, the authors demonstrated a negative association between community violence (including witnessing violence) as well as discrimination and mental health. Lund et al.

(2010) reviewed overcrowding and population density as commonly found in slums, to be negatively associated with mental health.

Health and social services

Riley et al. (2007) stated that while many economic activities such as electricity, water supply, or other private businesses can be operated and managed by the urban poor informally, health care is beyond the control of the urban poor. Health care requires, among other things, specialised, trained, and skilled personnel and medication, adequate infrastructure, prevention and surveillance. Furthermore, this service provides very few financial incentives. Often, pharmacies are the main source of health care in slums, offering only very basic and inadequate service from poorly or untrained personnel (Riley et al. 2007).

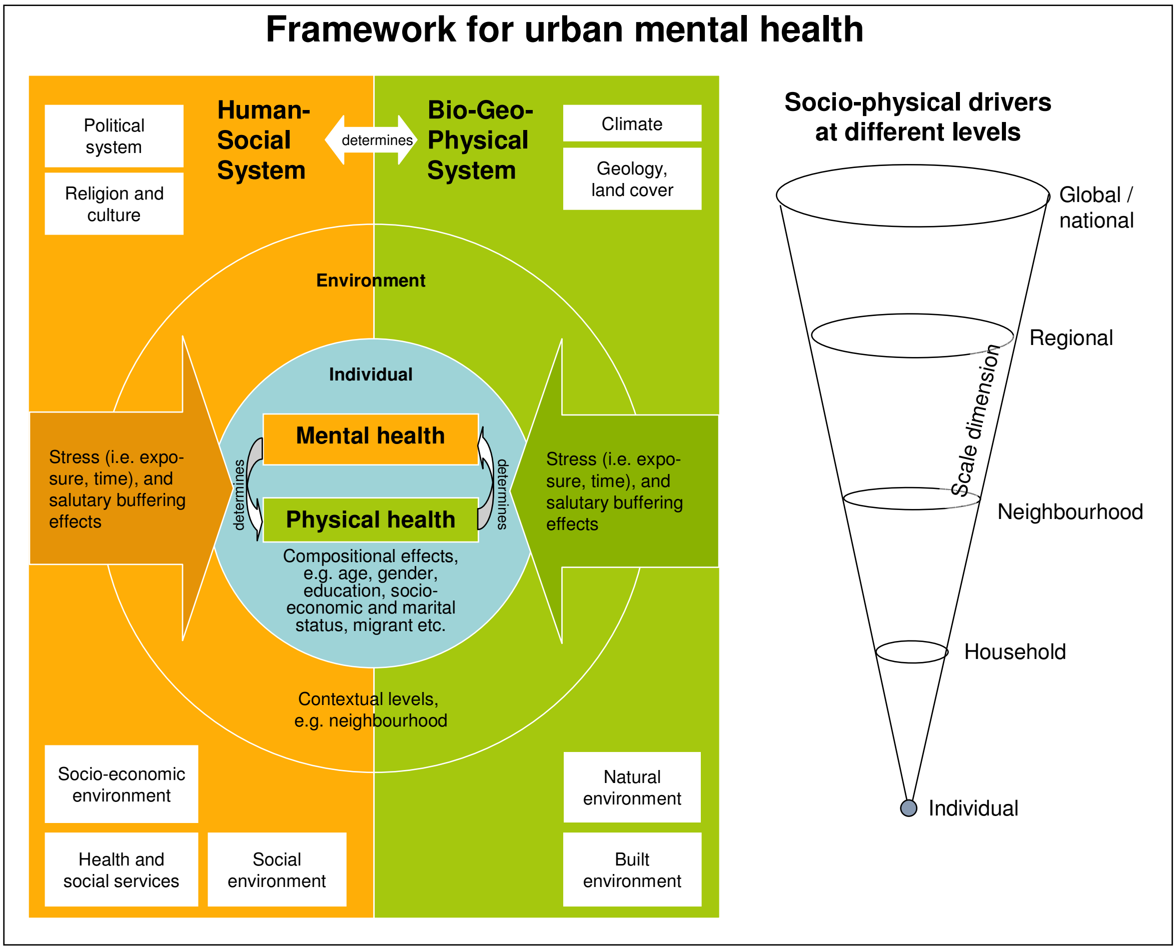

Figure II-2: Conceptual framework used for this dissertation. Source: Author's design. Whereas the political system or climate are conditions, structures, or processes working on global, national, or regional levels, the urban natural, built, or socio-economic environments determine health at lower levels (e.g., neighbourhood or household levels).

As Harpham (2009) reviews, the availability, access, appropriateness, and affordability of health services can vary greatly for underprivileged people. As reported, the urban poor must decide whether to utilise insufficiently supplied and poorly trained public sector health care resources or whether to spend a substantial part of their financial means for private health care facilities, often with no guarantee for better treatment.

3.2 The urban bio-geo-physical system and mental health

While economic and governmental systems, religion, or culture might be viewed as enduring social structures and conditions (Galea et al. 2005b), the geography of a country or region - such as the climatic zone or the geology - determines the physical condition in which local variations apply (Gruebner et al. 2011b). These enduring social and physical structures and conditions are expected to play a role in determining the neighbourhood environments in which local residents live. For an overview of how determinants can be conceptualised at different levels, please refer to Table II-3.

Climate

Global environmental change is a key challenge for the global community because it has international human dimensions. In addition to various ecological and economic ramifications, human well-being is profoundly affected by a changing climate. There is extensive evidence that climatic or atmospheric conditions have profound effects on human health (e.g., temperature affecting mortality rates), yet most studies are conducted in industrialised countries (Eurowinter Group 1997; Basu and Samet 2002; Rau 2006). In any case, the effect of meteorological conditions depends on the geographical region, the aligned macro- and mesoclimatic conditions, and the prevailing burden of disease, as well as socio-cultural and socio-economic aspects (Jendritzky 1992; Curriero et al. 2002; McMichael et al. 2008; Burkart and Endlicher 2009). All of these determinants are subject to spatial and temporal fluctuations and dynamics. Due to a lack of resources and data availability, little is currently known about the atmosphere-health relationship in tropical developing countries. In particular, the complexity of the matter requires a detailed and differentiated analysis. Additionally, in times of climate change, knowledge concerning the interdependencies among season, climate and health is gaining importance (Kalkstein 1993; Confalonieri et al. 2007; WHO 2009).

Natural environment

Large areas of vegetation and wetlands are generally known to provide important provisioning and regulating ecosystem goods and services (ESS), such as climate regulation, air, and water purification. These areas are therefore important features in the urban context (MA 2005). These goods and services can support health in a variety of ways (Corvalán et al. 2005). Urban green and park areas are typically considered to be recreational facilities for urban residents (Galea et al. 2005b; Alberti 2009) and increase the health-related quality of life and thereby mental health, for example, by reducing heat stress induced through a local urban heat island effect (Bowler et al. 2010; Burkart et al. 2011; Uejio et al. 2011). Burkart (2011) found that cardiovascular mortality in urban areas of Bangladesh showed a secondary maximum during the hot season, which underscores the relevance of the urban heat island as well as the increased vulnerability to heat in urban populations.

Built environment

Galea and Vlahov (2005) and Galea et al. (2005a) provided examples for the urban built environment and its relationship to mental health, albeit for cities in developed countries. However, Harpham (2009) argued that it is well accepted that factors from the built environment, such as water and sanitation, cause most child diarrhoea and contribute 4-8% of the global burden of disease. The author sees no further need to study these environmental health effects in urban areas of developing countries. However, she shows that poor quality housing conditions (cold, hot, or damp housing, mould, pest infection, lead paint, and overcrowded housing) are associated with health problems. Furthermore, she provides evidence (from developed countries) that increasing housing rents lead to increased stress levels and related poor mental health. Lund et al. (2010) also found that poor housing conditions were negatively associated with mental health in low- and middle-income countries.

Table II-3: Extended framework for urban health: multilevel effects of mega-urban environments related to human health. Source: Gruebner et al. (2011b).

Local context / Level	**Bio-Geo-Physical System**	**Human-Social System**
Enduring structures and conditions	- Climatic zone - Geology/Geomorphology	- Economic systems - Religion - Culture - Government
Global & national trends and dynamics	- Global climate change - Climatic seasons - Land use and land cover change	- Globalisation - Changing role of government - Immigration and migration
Regional/Municipal level determinants	- Urban ecological determinants o Provisioning and regulating ecosystem services o Urban fabric o Urban heat island effect	- Urban sociological determinants o Civil society o Markets o Municipal government
Neighbourhood/household level determinants	- Natural environment o Urban green/parkland o Air o Water bodies - Artificial built environment o Type of water supply o Type of sanitation o Type of housing - Noise	- Health and social services - Social environment o Social networks o Social capital o Segregation o Social support - Socio-economic environment
Individual level effects	Age, gender, education, health knowledge, marital status, place of birth, attitudes, behaviour, etc.	

Clougherty and Kubzansky (2010) argued that there is growing interest in disentangling the health effects of spatially clustered social and physical environmental exposures and in exploring potential synergies among these with particular attention directed to the combined effects of psychosocial stress and air pollution. Both exposures may be elevated in lower-income urban communities, and it has been hypothesised that stress, which can influence immune function and susceptibility, may potentiate the effects of air pollution in respiratory disease onset and exacerbation. In their paper, these authors reviewed the existing epidemiologic and toxicologic evidence concerning the synergistic effects of stress and pollution and described the physiologic effects of stress and key issues related to measuring and evaluating stress as it relates to physical environmental exposures and susceptibility. They recommend that careful attention be paid to the relative temporalities of stress and pollution exposures, to non-linearities in their independent and combined effects, to physiologic pathways not elucidated by epidemiologic methods, and to the relative spatial distributions of social and physical exposures at multiple geographic scales.

3.3 Individual level determinants

Although the health of a population is determined by a large number of factors (cf. Table II-3), placing emphasis on individual level determinants, such as age, education, marital status, behaviours, health competencies, and SES, is important because these are typical confounding factors[5] (Bonita et al. 2006; Merrill 2010). For example, gender-specific health determinants refer to the roles and norms of men and women in a given society. It is important to distinguish between women's and men's health and the role of gender as a social construct that shapes personal health behaviours and health-related societal structures (Ompad et al. 2007).

Education

Patel and Kleinman (2003) and Lund et al. (2010) indicated that illiteracy or poor education increases the risk for common mental disorders. Patel (2007) provided evidence for alcohol addicted males in India that also had lower education levels in comparison to non-hazardous drinkers. Further, education has been found to correlate with other health outcomes, income and wealth. Moreover, education provides the skills that enable the acquisition of economic, social, and psychological resources and can be associated with both negative and positive health outcomes (Ompad et al. 2007). However, the moderating (confounding) effect of education on the relationship between economic status and self perceived well-being decreases as education levels increase (Howell and Howell 2008). Patel and Kleinman (2003) further explored some confounding factors to determine the

[5]Confounding occurs when a variable is associated with both, the outcome, and independent of that relation, the exposure. For example, if age and gender are potential confounders between exercise and heart disease, focussing on men in their 50s could be a possible solution to prevent confounding (cf. Merrill 2010).

relationship between educational level and mental health. For example, malnutrition leads to poor psychosocial development and, thus, poor educational performance. Low income and its association with childhood psychiatric disorders are related to school failure and common mental disorders in adulthood. In turn, poor education increases the risk for dementia and also limits opportunities for individuals to gain access to resources that may improve the quality of their lives (Patel and Kleinman 2003). Harpham (2009) stresses the importance of community outreach workers in health education and social care, especially in developing countries.

Socio-economic status

Exposure to the socio-physical environment, for instance, can further be determined by SES that defines the frame of action within which an individual or household can respond to a health threat. In this context, resilience can be considered as the intrinsic ability of an individual or household to resist or cope with the impact of physical or social events (Villagrán De León 2006). Poor SES, low income, under- or unemployment, lower social class, and poverty were found to have a negative association with mental health according to various reviews of current research (cf. Patel and Kleinman 2003; Howell and Howell 2008; Harpham 2009; Lund et al. 2010). Howell and Howell (2008) further suggest that while gaining financial improvement and wealth, individuals also gain power, which, in turn, increases their resilience and ultimately well-being.

Lund et al. (2010) provided evidence that being unemployed or under-employed has a negative association with mental health, but this effect depends on local contextual factors. As these authors state, controlling for other variables such as age, gender, education, or physical health reduced the association between unemployment and mental health. Additional factors, which are also related to poor mental health, include food insecurity and financial stress, due to the constant worry of hunger and the uncertainty to afford food and other basic goods (Lund et al. 2010). Vijayakumar et al. (2005) further stated that low SES is a major reason for suicide in developing countries, particularly in countries where a welfare system is limited or non-existent.

Marital status

Egan et al. (2008) found some evidence for higher risks for poor mental health (bipolar disorder) for persons living alone in comparison to married couples or to persons living together. However, this information was primarily obtained in developed countries. Vijakumar et al. (2005) argued that for suicide, evidence supporting the notion that being single increases suicide risks comes mostly from developed countries. Yet, they did not find evidence for this causation in developing countries but (based on Indian examples) suggest that family and social ties are more important than marital status.

Community & religious participation

Egan et al. (2008) provided evidence that religious participation and religiosity are associated with mental health and that greater religiosity is related to fewer symptoms of depression. However, they also state that different forms of religiosity (attendance at church services or activities) were found to be associated with both greater distress and higher life satisfaction. Furthermore, for US Americans, Chavis and Wandersman (1990) found that a sense of community can have a catalytic effect on local participation in a community association by affecting perceptions of the environment, social relations, and one's perceived control and empowerment.

Migration

In developing countries, rural-to-urban migration is common (Caracci and Mezzich 2001) and induces stress for those who migrate (Bhugra 2004). Although not consistently, many studies have shown that common mental disorders are more prevalent among migrants in comparison to natives (Harpham 1994; Bhugra 2004; Harpham 2009) due to elevated stress levels, which may be induced through acculturative adaptation such as integration, assimilation, or rejection (Harpham 1994; Caracci and Mezzich 2001). Furthermore, racism or discrimination may also be an important factor when newcomers attempt to establish social, economic or political contacts (Bhugra 2004).

4 Conclusions

The key factors affecting mental health in cities can be considered within two broad themes: the human-social system and the geo-physical system, which comprise not only the socio-physical environment, including social, economic, and health and social services, but also the natural and built environment. These environments can affect the mental health of urban residents at different levels, underlining the need to study urban health in a multilevel and multi-sectoral way. While facing a double burden of ill-health, developing countries' megacities should be on the urban (mental) health research agenda and mental health should further be considered by development agencies and international initiatives such as the MDGs.

Chapter III: Spatial epidemiological applications in public health research

Why is a phenomenon distributed in a particular way?

(Meade and Earickson 2005: 10)

Taken from:

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Public health researchers are increasingly shifting their focus from models of disease epidemiology that focus exclusively on individual risk factors to models that also consider the complex and important effects of the socio-physical environment (Geanuracos et al. 2007). The application of spatial analysis in the context of epidemiological surveillance and research has increased exponentially (Pfeiffer et al. 2009). Geographic information systems (GISs), global positioning systems (GPSs) and remote sensing (RS) have been increasingly used in public health research since the 1990s (Kaiser et al. 2003). At the same time, geographers have started to extend their collaborations with public health researchers, building the still-young discipline of health geography[6] (Kearns 1993; Mayer and Meade 1994; Kearns and Moon 2002) which uses geographical concepts and techniques to investigate health-related topics (Meade and Earickson 2005; Gatrell and Elliott 2009).

Space, place and location have been extensively discussed within the context of health geography (Meade and Earickson 2005) and play a fundamental role in spatial epidemiological applications. For example, information about the positional location of a household or place is essential for spatial analysis, as is the extent of a region or space and socio-economic status, ill health, and personal perception that can be attributed to these locations. These attributes might then vary over space, time, and environmental exposure, and associated health outcomes will in turn differ with spatial and temporal scale (Galea et al. 2005b).

Research on the relationship between health and the environment requires multiple sources of data, which need to be integrated for analysis. GISs have been widely used by public health researchers because they provide a way to link individual health data to the physical space and social community within which a person lives (Edelmann 2007). With GISs, it is possible to describe the sources and geographical distributions of disease agents, to identify regions in time and space where people may be exposed to environmental and

[6] We refer to health geography, although there is a scientific debate on the naming of this discipline. Please refer to, e.g., Kearns (1993), Mayer and Meade (1994), and Kearns and Moon (2002) for arguments regarding whether to name it medical geography or the geographies of health.

biological agents, and to map and analyse spatial and temporal patterns in health outcomes (Cromley 2003). Understanding the spatial patterns of infectious diseases can provide insight as to their causes and controls (Ruankaew 2005). GIS approaches support deeper insights into how humans interact with their environment to promote better health (Ricketts 2003).

In this Chapter, we provide an overview of spatial applications in public health research. Focussing on both epidemiological and geographic research questions, we discuss methods and techniques that are suitable for assessing, managing, analysing, and visualising spatially referenced public health data. We underline our discussion with examples from an on-going research project focussing on health and the environment in the megacity of Dhaka, Bangladesh.

1 Spatial analysis using geoinformation technology

As one of the most important applications in spatial analysis, GISs cannot be regarded as one single tool or software. A GIS for public-health-related research for example, comprises a collection of compatible hardware, software (or algorithms) and methods for analysing spatial patterns of ill health and their mechanisms (risk factors, pathogens, resilience), as well as for producing maps and reports of spatialised public health information (Hostert and Gruebner 2010). Besides proprietary software like ESRI's ArcGIS™, GoogleEarth™, or GoogleMaps™, there is a wealth of open-source applications for different aspects of GISs, e.g., uDig, Quantum GIS, SAGA GIS, GeoDa, Open StreetMap, or spatial packages for the statistical environment R. FOSSGIS (2010) provides a comprehensive overview of up-to-date open source GIS software, data, documents and projects.

The science related to implementing and applying spatial methods with GISs is referred to as "GI Science" (Longley et al. 2007). Spatial epidemiological applications within GI Science and epidemiology can be grouped according to three types of study: disease mapping, exposure mapping, and spatial-epidemiological modelling with the aim of describing spatial patterns, identifying disease clusters, and explaining or predicting public health risk (Waller and Gotway 2004; Pfeiffer et al. 2009).

2 Data for spatial epidemiological analysis

Manifold data sources would be appropriate for analysis in a spatial context. However, geo-referenced data, e.g., statistics from official sources, is not always available, especially when the focus is on developing countries. However, there are ways to either collect one's own data or to link different kinds of data to perform spatial analysis. In either case, applications and analysis methods are highly dependent on the type, scale, and quality of the data at hand. Choosing a suitable method for analysing the data is often far from trivial, and common guidelines rarely exist. Here, we provide an overview of the most relevant data sets and related methods of analysis and discuss how this data can be integrated within GISs.

2.1 Survey data

Often, the type of data at hand determines the method to be used. For example, when data related to public health are available as point data representing all disease cases in a given study area and time period, the data may be analysed in a case-control setting. This involves the spatial variation of the cases being compared to the spatial variation of a background population (control group), with the null hypothesis assuming that the risk towards ill health is the same in all areas (constant risk hypothesis). The controls might either be assessed by conducting a census in the same area and at the same time or by considering other disease cases that do not have anything in common with the disease under investigation. For example, cases of a certain skin disease might sufficiently represent the background population when the spatial distribution of respiratory disease cases is under investigation (Waller and Gotway 2004).

A GPS-based health survey conducted in, for example, a cross-sectional fashion, delivers health information of a "slice" of the investigated population, assuming the sampled subpopulation to be representative for the whole group. The resulting data set is thus a sampled point data set with information on health status, individual factors and, sometimes, other physical and social environmental variables that are thought to affect the respondents' health. However, this kind of data remains rare because data sets are often aggregated for privacy reasons and health information is only available for enumeration areas, zip codes, or other administrative units. Statistical methods are therefore often chosen to suit either case-control point data that represents (all) disease cases in a study area, or to suit aggregated data in the form of disease counts (i.e., the number of disease cases, rates, or ratios). In this context, rates are the cases per person at risk, and ratios are the number of cases compared to the number of controls for arbitrarily chosen area units.

2.2 Remote sensing based data

Remote-sensing-derived information is becoming increasingly available worldwide and at multiple scales. Today, GI Science strives to better integrate information derived from remote sensing in its various analytical processes. Moreover, methods from GISs are increasingly integrated with digital image processing methods for analysing remote sensing data. Lillesand et al. (2003) provide a well written introduction to remote sensing and image interpretation appropriate for non-remote sensing scientists. For details on digital image processing in remote sensing, we suggest Richards and Jia (2005) as introductory reading.

Remote sensing from airborne and satellite platforms provides spatially continuous data at different scales. While the mere image data can serve as a cartographic base map or image backdrop for visualisation, we are usually interested in problem-specific information derived from remote sensing imagery. Raw image data are turned into information layers via image interpretation or digital image processing. This can, in turn, be integrated into a complex analysis of health and the environment.

Typical remote-sensing-derived information for public health research comprises land use and land cover, vegetation type or habitat maps, water maps or diverse structural surface properties (e.g., information on infrastructure or corridors such as vegetation, airflow, etc.) to be used in exposure mapping. Additionally, more sophisticated products, such as indicators on housing structures in slum settlements or indirect estimates of population density, may be derived in cases where adequate statistical data are missing or erroneous. In other words, remote sensing can provide information urgently needed on the explanatory side of the equation linking health and the environment.

3 Data integration for public health research

In GISs, data integration is straightforward owing to the combined use of spatial databases, geovisualisation and geoprocessing tools (Hostert and Gruebner 2010). Within spatial databases, for example, the data can be structured, documented, and also linked to data available from other sources.

Research on health and the environment in urban areas, for example, requires multi-source data that need to be combined for analysis. A spatial database can be developed for solving urban public health questions and can be structured to incorporate data on the social and physical environment as well as data on individual factors determining public health. The most important benefits of a database are that it can guarantee data integrity and data redundancy and prevent data inconsistency. Moreover, it can prevent problems with multi-user applications and data loss and ensure data security. This can be made possible through the use of a data model[7] with database relations in the normal form[8]. While data are stored in numerous tables with atomised attributes in the GIS database, GIS-based analyses are performed via more convenient "table views". In such table views, attributes (e.g., health outcomes, traffic emissions or birth rate) can be rigorously combined with GIS features (i.e., a point, line or polygon) representing the location of households, streets or administrative boundaries for spatial epidemiological analysis. Furthermore, with web features and web map services, it is possible to combine the local data set with data available from other sources via the Internet. For a complete discussion of data integration within GI Science, refer to Longley et al. (2007).

4 A conceptual framework for spatial epidemiological analysis

There is a wealth of publications that consider spatial analysis and public health research, focussing on either statistical models or applications within specific scientific fields. We draw on the work of Elliott et al. (2006), Gatrell and Elliott (2009), Pfeiffer et al. (2009), and Waller and Gotway (2004) and provide a comprehensive framework to structure the

[7] A data model is an abstract model describing how data are structured. Data models are used to integrate different kinds of information, putting them into a thematic, semantic or – in the case of spatial data – a geometric-topological structure.

[8] A relation R is in the first normal form (1NF) if all underlying domains contain atomic values only. A relation R is in the second normal form (2NF) if it is in 1NF and every non-key attribute is fully dependent on the primary key. A relation R is in the third normal form (3NF) if it is in 2NF and every non-key attribute is non-transitively dependent on the primary key. Two more NF exist but are rarely implemented because the data structure then often ends up in overly flat tables.

available methods and guide researchers in finding a suitable approach for analysing their data.

Our framework includes three key pillars:

- Disease mapping
- Exposure mapping
- Spatial epidemiological modelling

For the spatial and temporal analysis of health outcomes, one can draw on the rich framework of spatial statistics that has been developed over the last 50 years (Fortin and Dale 2006, p. 25). Spatial autocorrelation analysis is one method used to discover the extent to which given observations can be regarded as spatially independent or clustered (Tobler 1970). Test statistics are used to detect the patterns of, for example, ill health in space and time, which can provide insight into causes and controls (Ruankaew 2005; Hostert and Gruebner 2010).

Spatial autocorrelation analysis is based on adjacency or distance measures and therefore depends on neighbourhood definitions. Neighbourhood definitions specify which sample points are considered to be neighbours (i.e., based on adjacency or a fixed distance band), while spatial weights specify whether all neighbours should be treated the same way or whether some of them have a greater importance than others due to shorter distances between them (Waller and Gotway 2004). A number of different approaches exist to specify neighbourhood relationships and spatial weights. Because model outcomes are sensitive to the approaches used and no theoretical guidance exists as to which approaches should be selected, we suggest following the guidance from Bivand et al. (2008): use and compare a set of approaches including *k*-nearest neighbours and distance-based approaches. Finally, a closer look at the research question at hand can help to define the appropriate method for assessing neighbourhood relations. For example, if our research targeted an infectious disease, comparing the spatial variation of the disease between a city area and a sub-urban area, we should choose a spatial weights neighbourhood (i.e., distance-based) relation. In this approach, greater importance would be given to those neighbours that are closer in space than others. This allows the best representation of the spatial variation of the background population at risk of contracting a certain disease when the population is heterogeneously distributed, with higher concentrations in the city than in the surrounding areas.

Fundamental to the analysis of spatial patterns is consideration of the spatial processes creating the pattern. Stationarity, isotropy, first-order (trend), and second-order (local) spatial effects are related concepts. In brief, a spatial process is termed stationary if the dependence between measurements of the same variable across space is the same for all locations in an area. The distance dependency of the variance of the variable under study might vary with direction. In this case, the process is called anisotropic; otherwise, it is isotropic. First-order effects describe large-scale variations in the mean of the outcome of interest due to location or other explanatory variables, while second-order effects describe small-scale variation due to interactions between neighbours (Pfeiffer et al. 2009).

Statistical significance tests

Statistical significance of most tests for spatial autocorrelation can be assessed by a randomisation procedure (Monte Carlo test). If specific assumptions are met, a normal approximation distribution test could be used as an alternative. During the randomisation procedure, data values are reassigned among N locations, providing a randomisation distribution against which one can judge the observed value. If the observed value of the test statistic lies in the tails of this distribution, one can say that there is significant spatial autocorrelation in the data to reject the assumption of independence among the observations. Another option is to compare the Z-score (standard deviation) to a standard normal distribution because the Z-score can be assumed to have an approximately normal distribution (Cliff and Ord 1973; Cliff and Ord 1981). In general, however, the randomisation test is the preferred procedure.

5 Disease mapping

Disease mapping can be defined as the spatial and temporal estimation and presentation of health outcomes with the aim of cluster detection, assessing health inequalities, generating hypotheses, and estimating spatial variability in underlying risk for ill health (Elliott et al. 2006).

For example, the risk of ill health represents the probability of a person contracting a disease within a specified time period. Risk is an attribute of a person and is determined by endogenous characteristics such as age, gender, and education, and by exogenous socio-physical environmental factors such as occupation, living conditions, and social network, amongst others. Risk is an unobserved and dynamic quantity to be estimated.

In the following, we focus on global measures that enable tests for spatial autocorrelation over the whole study area and on local indicators of spatial associations (LISA), which provide information about the type of clustering and the locations of clusters (Anselin 1995). While we can only present an overview of existing methods here, the interested reader is referred to Bivand et al. (2008), Pfeiffer et al. (2009) and Waller and Gotway (2004).

5.1 Global estimates of spatial autocorrelation

Global autocorrelation methods are used to assess whether significant spatial patterns are apparent throughout the study area. However, these do not help to identify the location of spatial patterns. The null hypothesis is that no spatial pattern exists (Pfeiffer et al. 2009).

Keeping the population at risk and corresponding neighbourhood relations in mind, several methods of spatial autocorrelation analysis are available. Depending on the data on hand, the *k*-nearest neighbour test (Cuzick and Edwards 1990), the *K*-function (Ripley 1977), and the cumulative sum statistic (Rogerson 1997) are qualified for case-control point data. For aggregated data and sampled point data, Moran's *I* (Moran 1948, 1950), Geary's *c* (Geary 1954), Tango's index (Tango 1995), and Whittemore's method (Whittemore et al. 1987) are suitable. When trying to determine whether a disease is infectious, it is important to consider space-time clustering detection methods. It is crucial to gain knowledge about whether disease cases that are close in space are also close in time and vice versa. Global space-time clustering detection tests include the space-time *k*-function (Diggle et al. 1995), the Ederer-Myers-Mantel test (Ederer et al. 1964), Mantel's test (Mantel 1967), Barton's test (Barton et al. 1965) and Jacquez's *k*-nearest neighbour test (Jacquez 1996).

5.2 Local estimates of spatial association

While global measures enable testing for spatial patterns over the whole study area (first-order effects), local indicators of spatial associations (LISA) test for statistically significant local spatial patterns (Anselin 1995). Hence, local methods of spatial association define the type, location and extent of spatial patterns such as clusters and describe second-order effects in the data. The primary goal of such methods is to determine where the observed value, rate, or ratio differs significantly from the value, rate, or ratio observed over the rest of the study area (Waller and Gotway 2004). Some authors further divide local methods into focussed and non-focussed tests for detecting clusters. Non-focussed tests identify the location of all likely clusters in a study area, while focussed tests investigate whether there is an increased risk around a pre-determined point, such as a source of air pollution (Pfeiffer et al. 2009). Local estimates of spatial associations can be further divided into distance- and adjacency-based approaches, like the global measures, and into moving window-based approaches, which are typically local measures for case-control data (Elliott et al. 2006). With moving window-based approaches, circular windows of varying radii are applied over the study area to compare the observed number of disease cases with the expected number of cases, assuming that the process under investigation follows a Poisson process (Pfeiffer et al. 2009).

For case-control point data, moving window-based approaches like the Geographical Analysis Machine (Openshaw et al. 1987), the Cluster Evaluation Permutation Procedure (Turnbull et al. 1990), the Spatial Scan Statistic (Kulldorff 1997), Besag and Newell's method (Besag and Newell 1991) and the Rushton and the Lolonis Disease Mapping and Analysis Program (Rushton and Lolonis 1996) are suitable for detecting clusters. Local measures for point data also involve focussed tests for including explanatory variables in a model to explain the health status of the population by distance from a putative health threat. Health data (the disease) and exposure data (a certain point in space contributing to the disease) are modelled to investigate the association of the point source, distance and the corresponding disease. Focussed tests for detecting local clusters include Stone's test (Stone 1988), Lawson and Waller's score test (Waller et al. 1992; Lawson 1993), Bithell's linear risk score test (Bithel et al. 1994; Bithel 1995), and Diggle's test (Diggle 1990). For the detection of local clusters in space and time, Kulldorf (2001) proposed the Space-Time Scan Statistic.

For aggregated data and sampled point data, the moving window-based methods above will also be suitable. Additionally, distance and adjacency based approaches like the Anselin Local Moran's *I* (Anselin 1995), and the Getis Ord Gi* (Getis and Ord 1992) are found to be qualified for spatial pattern detection (Waller and Gotway 2004; Elliott et al. 2006; Pfeiffer et al. 2009).

With local spatial autocorrelation tests, we can describe second-order effects of the spatial process such as small-scale variation due to interactions between neighbours. However, the moving window-based local spatial pattern detection methods work with circles and thus assume that disease clusters are circular. Moreover, another limitation of window-based spatial autocorrelation tests is the *a priori* choice of cluster size. Testing for a variety of cluster sizes results in problems of multiple inferences, although this can be accounted for with a Bonferroni correction (Pfeiffer et al. 2009).

5.3 Spatial variation of risk for ill health

The final goal of disease mapping is often to provide maps showing the spatial variation of the population at risk for ill health. These maps provide important evidence for disease causes and controls; thus, they can ideally inform policy in a concise, synoptic way. For example, the information presented may include the density of disease cases or standard mortality/morbidity ratios (SMR). The objective is to show the important spatial effects present in the data. The resulting smoothed map should have increased information content without introducing significant bias. Again, the data at hand determine the methods used for producing the maps. For point data, kernel-smoothing methods would be best to facilitate visual assessment of the pattern. Bayesian methods are best suited for aggregated data, like SMR, to account for the uncertainty of local measurement and spatial dependence between neighbouring measurements (Pfeiffer et al. 2009). For a more in-depth discussion of how these methods work, the reader is referred to Elliott et al. (2006), Lawson et al. (2003), Lawson (2009), Pfeiffer et al. (2009), and Waller and Gotway (2004).

6 Exposure mapping

Exposure modelling and mapping can be defined as the spatial and spatio-temporal estimation and presentation of factors from the social or physical environment that are (thought to be) associated with health outcomes (Elliott et al. 2006).

Various methods exist with which to analyse the manifold factors contributing to ill health. While spatial autocorrelation analysis can also be applied to exposure data, here we focus on methods for the geoprocessing of exposure data and present the most typical methods available in GIS.

Topological analysis

Topological analysis is based on the fact that each feature (point, line or polygon) "knows" its geographic coordinate and its neighbouring features (adjacency). This is achieved by incorporating topological information into the spatial data model. It is then possible to easily and quickly track all connected features (e.g., shared borders) between adjacent areas. For example, when a point is connected with a line and this line is connected with another point, topology infers that both points are also connected (connectivity) and analysis procedures can use this information in an automated way. Topology can also be used to detect features lying in a polygon (containment). Additionally, attribute data can be used in a spatial database query such as, “Which housing is adjacent to an industrial area with recorded blood cancer or respiratory disease cases?”

Overlay analysis

Spatial relationships between different data sets can be discovered and new layers with a higher level of information content created from their joint analysis. Vector (topological) overlay functions include “intersect”, “union”, and “clip”. “Intersect” is used to combine two data sets and to preserve those features and attributes falling in the spatial extent of both layers. In contrast, “union” generally keeps all features of both data sets. With the “clip” function, one portion of a layer is cut using another layer as a kind of “cookie-cutter”. For detailed information on how these functions work and how they are used, see Longley et al. (2007). Raster overlay deals with cell values from different raster grid scenes that can be combined via mathematical operations (map algebra) to generate new values of cells at corresponding positions in a new grid layer (Boulos et al. 2001; Boulos 2004).

Interpolation

Interpolation methods that derive spatially continuous information from spatially discontinuous point data are needed to relate point-sampling data on diseases with explanatory information sampled at different locations. Sometimes it is necessary to achieve a spatially continuous map surface from a point data set with information on phenomena that are also spatially continuous, such as precipitation measures or ozone values. In these cases, interpolation can help to estimate the values for in-between locations for which no measurements are available. “Kriging”, for example, is an established method for producing such continuous map surfaces from point data sets (Cromley and McLafferty 2002). Kriging uses the underlying spatial structure of the sample data (distances among samples or observations) to estimate parameters that describe the spatial structure of the data. This distance-based functional relationship is then used in a weighted moving average approach to predict values and standard errors for no-sample locations.

Proximity analysis

Proximity analysis works with so-called buffers that are drawn around a point, line or polygon. These buffers can measure distances to known pollution sources or quantify the population at risk. By including thematic information, proximity analysis can be used to stratify data. The population at risk may be divided into age groups, or quartiles of age distributions may be used to derive buffer zones with equal proportions of certain age groups.

7 Spatial epidemiological modelling

We define spatial epidemiological modelling as quantifying and predicting the spatial distribution of a particular health outcome by a set of exogenous explanatory variables from the socio-physical environment and endogenous individual-level factors.

Analytical models are a means with which to quantify the effects of explanatory variables on health outcomes, while simulation models are used for predicting health outcomes. In this section, we review solely analytical models. The interested reader is referred to Maguire et al. (2005) for a profound discussion of simulation models.

A wide variety of analytical model approaches exists. Linear and generalised linear models are the most widespread types of models used to describe empirical relationships between health outcome and explanatory variables. Depending on the properties of the data, Gaussian, Poisson, negative binomial, binomial and other kind of distribution families can be used to properly fit the model to the data (Waller and Gotway 2004).

Multivariable models are applied to provide both a means of quantifying first-order effects and, once first-order effects have been considered, second-order effects. If only one explanatory variable is to be used, the bivariate Moran's *I* statistic can be considered. The statistic is good at gaining information on the extent to which values for the outcome variable observed at a given location show a systematic (more than likely under spatial randomness) association with another variable observed at the "neighbouring" locations. This bivariate spatial correlation can be considered in addition to, or instead of, the usual (non-spatial) correlation between two variables at the same location (Anselin et al. 2002).

Residuals from multivariable regression models can be examined for evidence of spatial autocorrelation to identify the presence of second-order effects. If there is no evidence of autocorrelation in the residuals, the data are most likely not spatially structured and a non-spatial model should provide a satisfactory description of the data. However, there may also be some non-spatial effects. Regression approaches for spatially independent data include linear regression models or additive models (GAM) (Waller and Gotway 2004; Pfeiffer et al. 2009).

If a second order spatial pattern is evident in the residuals, the model has to be extended to account for the spatial dependency in the data. Mixed models, for example, provide a means to account for dependencies because they consist of a fixed part and a random part. The fixed part describes the response variable as a function of the explanatory variables. The random part contains components that allow for heterogeneity[9], nested data (random effects), spatial or temporal correlation, and a real random term (Zuur et al. 2009). Thus, the random part allows for a correlation of the response variable. Mixed modelling approaches take into account the clustered structure of the data, assuming that individuals are nested within households, households are clustered within neighbourhoods, neighbourhoods are located within settlements, and so on. Subjects from within the same cluster will be more similar than subjects from different clusters due to their shared environment. In this way, mixed effects models regard spatial proximity as a form of multilevel clustering (Pfeiffer et al. 2009).

For a in-depth discussion of how these models work, the interested reader is referred to Dormann et al. (2007), Waller and Gotway (2004), and Zuur et al. (2009).

8 Summary

Spatial epidemiology within GI Science is an emerging field and can be based on established concepts and methods from the areas of public health, epidemiology, spatial statistics and geography. We provided examples that demonstrated how to apply remote sensing and enrich survey-based, geo-referenced data in GISs. We further showed how geoprocessed data could be analysed through simple disease and exposure mapping, as well as through a simple spatial epidemiological approach. We are well aware that these

[9] Heterogeneity, the violation of homogeneity, happens if the spread of the data is not the same at each X value. This can be checked by comparing the spread of the residuals for the different X values (Zuur et al. 2009).

examples can only provide the beginnings of an understanding of the methods and applications available within the field of spatial epidemiology. However, we hope that we were able to provide some new ideas to colleagues from related research fields. Collaborative efforts between epidemiologists, biostatisticians, environmental scientists, GI Science experts, and health geographers are needed to realise the full potential of spatial epidemiology in environmental health research. This may then lead to innovative solutions to complex questions.

Chapter IV:
Research area and data

1 Geography of Bangladesh

Bangladesh is located in South Asia and shares its borders mostly with India. Burma is located to the southeast of Bangladesh, and the Bay of Bengal forms the natural delimitation of the country to the south (cf. Figure IV-1). Bangladesh lies within one of the world's largest river deltas, formed by the rivers Ganges, Brahmaputra and Meghna and their respective tributaries. The alluvial terrace formed by the deposit of these rivers is known as the Madhupur Terrace and is one of the most fertile plains of the world. Bangladesh has a tropical climate with a mild winter from October to March, a hot, humid summer from March to June, and a warm, humid monsoon season from June to October. The majority (80%) of the country's 2000 mm annual rainfall comes during the monsoon season. Natural calamities, such as tropical cyclones, tidal bores, and floods, occur almost every year. Bangladesh is recognised as one of the countries most vulnerable to climate change. Heavy downpours, sea level rise, and snow melt in the Himalayas are expected to increase in a changing climate, with devastating consequences for public life and human health (Gruebner et al. 2011b). Ahmed and Falk (2008), for example, showed the effects of global climate change for Bangladesh. Salinisation of agricultural fields is increasing in pace in the south of the country due to the rise in frequency of cyclones. Hence, an increasing number of climate refugees are expected to move from agricultural areas to the major cities.

With a population of approximately 159 million inhabitants (Germany: 82 million) and restricted land availability due to its large river system, Bangladesh is one of the most densely populated countries in the world (CIA 2011). There are 1,218 inhabitants per km^2, (Germany: 234 inhabitants per km^2) (ibid). The country has a constitutional democracy, though it cannot yet be considered consolidated (IGS 2010). Poverty, social inequality, and a political class known for its corruption, weak institutions, and mismanagement have brought about public mistrust and social tension (Siddiqui et al. 2004; IGS 2010). With a liberal but weak economic system and a GDP per capita (PPP)[10] of 1,700US$ (Germany: 35,700US$) (CIA 2011), Bangladesh provides hardly any state-driven social insurance and no health insurance for its citizens (Islam 2005). However, an economic trend can be identified in the flourishing export-oriented garment industry. More than 800,000 of the capital city's inhabitants are employed in this sector, producing labour-intensive goods under poor working conditions (Kabeer and Mahmud 2004).

[10] Gross domestic product (GDP) on a purchasing power parity (PPP) basis divided by population as of 1 July for the same year.

Figure IV-1: Map of Bangladesh. Source: UN (2004).

2 Health survey

2.1 Study design

We conducted a one-year cohort study in nine slums of Dhaka in 2009. We analysed data from 1,938 adults (male=48% and female=52%) aged 15 to 99 years; some respondents were excluded because they were <15 years of age. Trained university graduates performed the face-to-face interviews.

We extensively discussed the aims and objectives of the survey with local community leaders first, and when an agreement was reached, we invited the residents to participate.

We then discussed the aims of the survey with potential interviewees and proceeded only when their verbal consent was given. As such, every respondent participated voluntarily in the survey, and answers could be declined as inappropriate. The interviews were conducted in the residents' private dwellings. However, we could not always guarantee that neighbours were not present at the time the interview was conducted. We did not use any medical equipment, collect any blood, or provide any placebo medicine. All information (e.g., health status, height, and weight) was self-rated by the respondent. Although various types of information were collected, only some relevant variables are used in this thesis. We used global positioning systems (GPS) to record the location of each interviewed household. However, this information was stored separately from the survey data and was only used anonymously in further analysis.

2.2 Sampling strategy for slums and households

Approximately 4,900 slums were identified by the Centre for Urban Studies (CUS et al.2006). We established minimum threshold values of 500 households and six acres per slum to select comparable slum settlements from the CUS survey. To achieve an equal geographical distribution of the slum settlements, we subsequently selected administrative units that were not next to one another. In units with more than one slum, we randomly selected one of these settlements. We also adapted our selection to account for slums that were evicted or became affluent residential areas or open spaces during the study period (cf. Figure IV-2).

2.3 Sampling strategy for participants within slums

Using equations 1 and 2 from Bartlett et al. (2001), we estimated the minimum number of families (sample size) within each of the slum settlements (n_{pop}).

$$n_{\text{inf}} = \frac{Z^2(p)(1-p)}{d^2}$$, where (Equation IV-1)

n_{inf} = sample size for an infinitive population,

Z= quantile value of the normal distribution for the selected confidence level,

p = probability of selecting an individual with a certain health status (e.g., WHO-5 score ≤13), and

d = acceptable margin of error as a percentage,

$$N = \frac{n_{\text{inf}}}{(1 - \frac{n_{\text{inf}}}{n_{pop}})}$$, where (Equation IV-2)

N = sample size (for a finite population).

In our study, we used a 95% confidence level and an error margin of d=6%. Because it was not possible to run a pilot study to determine an estimate for p, we used a 50% chance of choosing the "right" sample (p=0.5). To calculate the sampling rate r, we divided the number of families in the slum by the calculated sample size. We then interviewed every r^{th} household using systematic sampling. When it was not possible to identify an interviewee at a household, we proceeded with the next family.

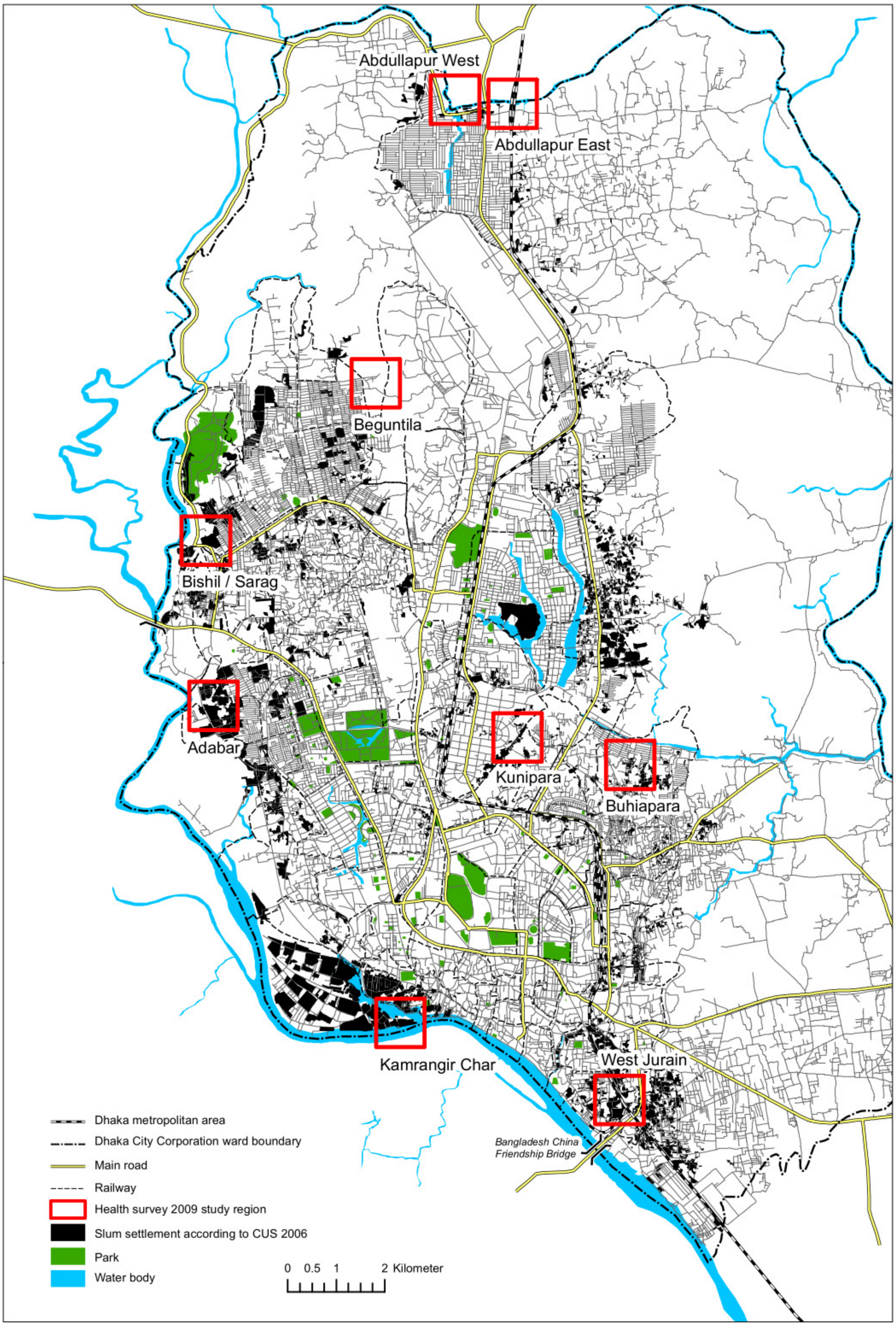


Figure IV-2: Dhaka city cohort study 2009 and corresponding slum settlements.

2.4 Health measures

We used five forced-choice Likert-scaled (Likert 1932) questions (from zero to five) to derive the WHO-5 (cf. Table IV-1). The five questions were summed up in an index ranging from 0 to 25 (WHO 2010). The WHO-5 is commonly used as a screening instrument for depression (Bonsignore et al. 2001) and self-rated quality of life. Generally, WHO-5 values below 13 indicate poor mental health (WHO 2010). WHO-5 is a quick, reliable, and valid measure for assessing psychological well-being or depression (Bonsignore et al. 2001; Delaney et al. 2007; Barua and Kar 2010; Newnham et al. 2010). The index is easy to assess because it contains only five questions, which is fewer than other tools such as the Beck Depression Inventory, with 21 questions (Kerr and Kerr 2001); the Centre for Epidemiological Studies Depression Scale (CES-D) (Rahman and Rollock 2004), with 20 items; the General Health Questionnaire (GHQ-12), with 12 questions; or the Patient Health Questionnaire with 9 questions (PHQ-9) (Henkel et al. 2003). The WHO-5 can thus easily be extended to a larger sample of the slum population. It has been successfully applied in both developed (Henkel et al. 2003; Kessing et al. 2006; Awata et al. 2007; Liwowsky et al. 2009) and developing countries (Saipanish et al. 2009; Barua and Kar 2010; Momtaza et al. 2011). Although the WHO-5 has not yet been validated in Bangladesh, it was found reliable and effective among elderly Indian communities (Barua and Kar 2010), which are socioeconomically similar to Bangladeshi communities.

Table IV-1: The WHO-5 Well-being Index. The questions could either be rated as: All of the time (5), most of the time (4), more than half of the time (3), less than half of the time (2), some of the time (1), or at no time (0). Please see appendix Figure A-1 for more information.

	Over the last two weeks
1	I have felt cheerful and in good spirits
2	I have felt calm and relaxed
3	I have felt active and vigorous
4	I woke up feeling fresh and rested
5	My daily life has been filled with things that interest me

Additionally, we asked respondents how they rate their health with the possible aggregated answers “poor” and “fair” (1), “so-so” (2), “good” and “excellent” (3). We subsequently term this variable “self-rated health” or SRH. As a third measure for health status, we asked whether respondents had suffered from any disease in the three months preceding the survey, coded as 1 for yes and 0 for no, and shortly termed “disease”.

3 Explanatory variables

Baseline data from the cohort study were used. We structured the variables according to the bio-geo-physical and the human-social environment. We conceptualised the variables at three different levels: the neighbourhood, the household, and the individual level. However, they were measured and analysed at the individual level (cf. Table IV-2 for the variables used in this thesis).

Table IV-2: Explanatory and target variables selected for analysis. All variables were gained through our health survey in 2009.

Level	Bio-geo-physical system	Human-social system
Neighbourhood	**Natural and built environment** o Is your area flood-affected? o Does your area have a proper drainage system?	
Household	**Built environment** o Monthly rent for the house (in Taka) o Family has household item: o Radio o TV o Gas burner o Electric fan o Tape/CD/VCD o Refrigerator o Is there sufficient light in your room/house? o Is your house provisional or permanent? o How many rooms do you have? o Is your room/house also used for purposes other than living? o Is your room/house sufficient for your family? o What kind of material do you normally use for cooking? o Housing quality o Type of water supply o Type of toilet facility o Type of garbage disposal	**Social environment** o Family size o Persons living in the same room o Persons sharing same meals **Economic environment** o Number of family members who earn income o Monthly family income (in Taka) o Do you have a job contract? o How many hours do you work per day? o Do you think your job is harmful for your health? o How do you like your job?
Individual	**Health knowledge and behaviour** Do you think that: o … smoking tobacco is bad for your health? o … physical exercise is good for your health? o … polluted or logged water/garbage near the house spread disease and increase the risk of poor health? o …air pollution is bad for your health? o Do you smoke cigarettes?	

- o Do you smoke inside your room?
- o How many family members smoke?

Personal characteristics

- o Are you engaged in community activities?
- o Do you use a bed net?
- o How many years did you spend in school?
- o Are you married?
- o Migration status (based on place of birth)
- o Age
- o Gender

Health outcomes

- o WHO-5 Well-being Index
- o Self-rated health
- o Disease

3.1 Neighbourhood and household level

Natural and built environment

Around 70% of the respondents reported that their living area was flood-affected, and more than 80% said that there was no adequate drainage system in their neighbourhood (cf. Figure IV-3).Most of the respondents had to pay less than 11 US$ per month for their housing rent (assuming 1US$ = 70 Bangladeshi Taka). Most of the households had an electric fan, and only 1.5% of the respondents had a refrigerator.

Moreover, slum dwellers were often residing in rooms or houses without any sufficient light (cf. Figure IV-4). Around 90% of the respondents were living in temporary houses, and more than 70% had only one room for living, which was also used for purposes other than living by 30% of the slum dwellers. Around three-quarters reported that their room/house was not sufficient for their family, and more than half of the respondents were cooking with straw, dry leaves, cow dung, or wood, which could create high levels of air pollution. Only a few houses were constructed of high-quality, durable materials. For instance, only a third of all respondents lived in durable *pucca* (i.e., made of bricks and cement) houses. Half of them lived in non-durable *semi-pucca* (i.e., made only partially of tin and bricks) houses, and a fifth lived in fragile *kutcha* (i.e., made of clay, bamboo and/or jute) houses. Respondents' water supply was mostly piped water, and about two-thirds of the respondents only had pit latrines. Moreover, garbage disposal was most often in an open space in the neighbourhood; only 7% reported regular collection of their garbage.

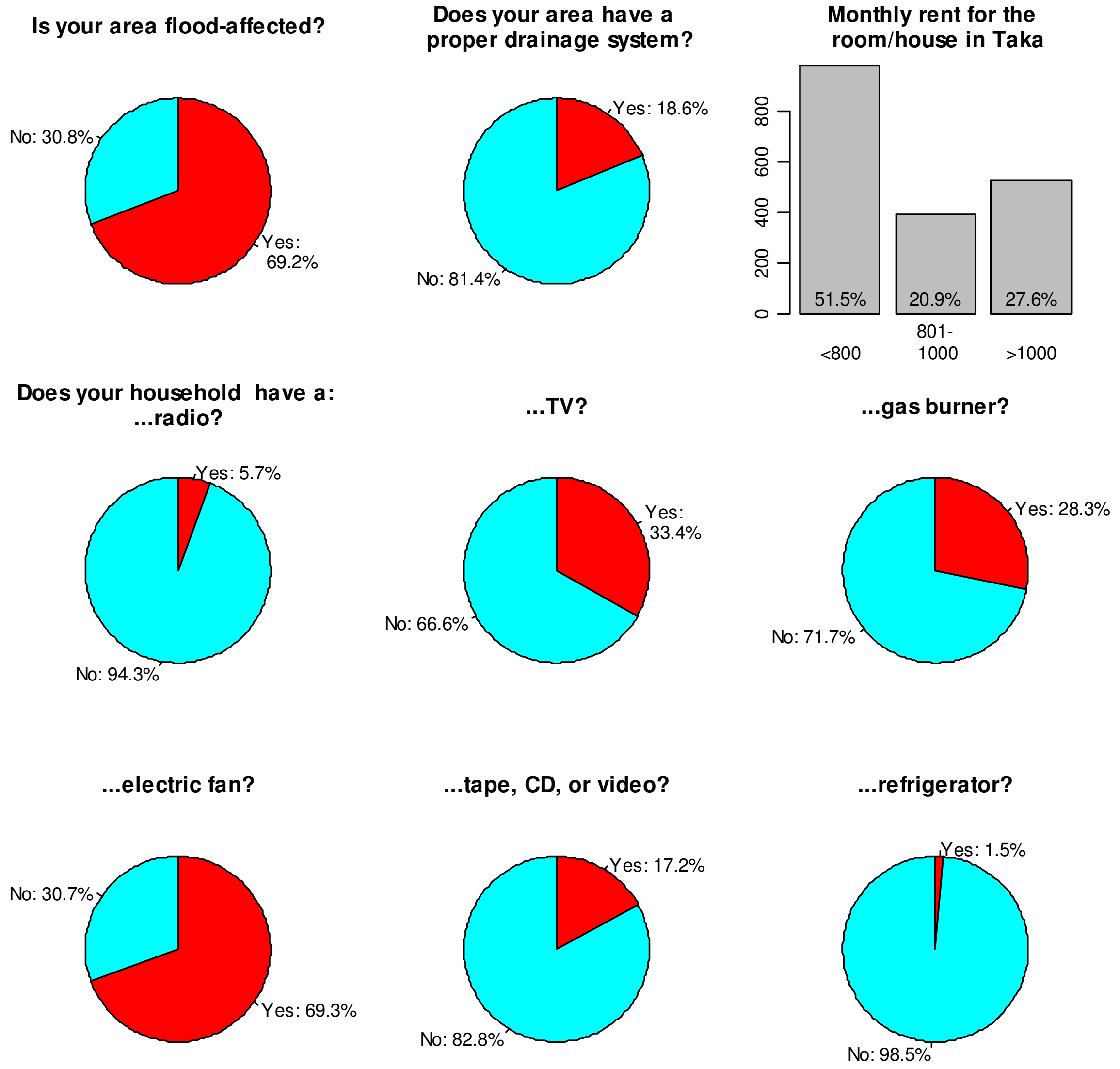


Figure IV-3: Environment-related information and household items of slum dwellers in Dhaka.

Socio-economic environment

More than half of the respondents reported 3-5 family members who were living in the same room and sharing the same meals (cf. Figure IV-5). Most respondents reported that only 1 or 2 family members were earning income. About 60% of respondents' families had an average monthly income of less than 7000Taka (26 US$). Very few of the respondents had a job contract, and more than half of the male respondents reported that they have to work more than 8 hours a day. More than three-quarters of the respondents considered their workplace harmful to their health. Further, more females reported poor working conditions than males. However, most of the respondents said they liked their job.

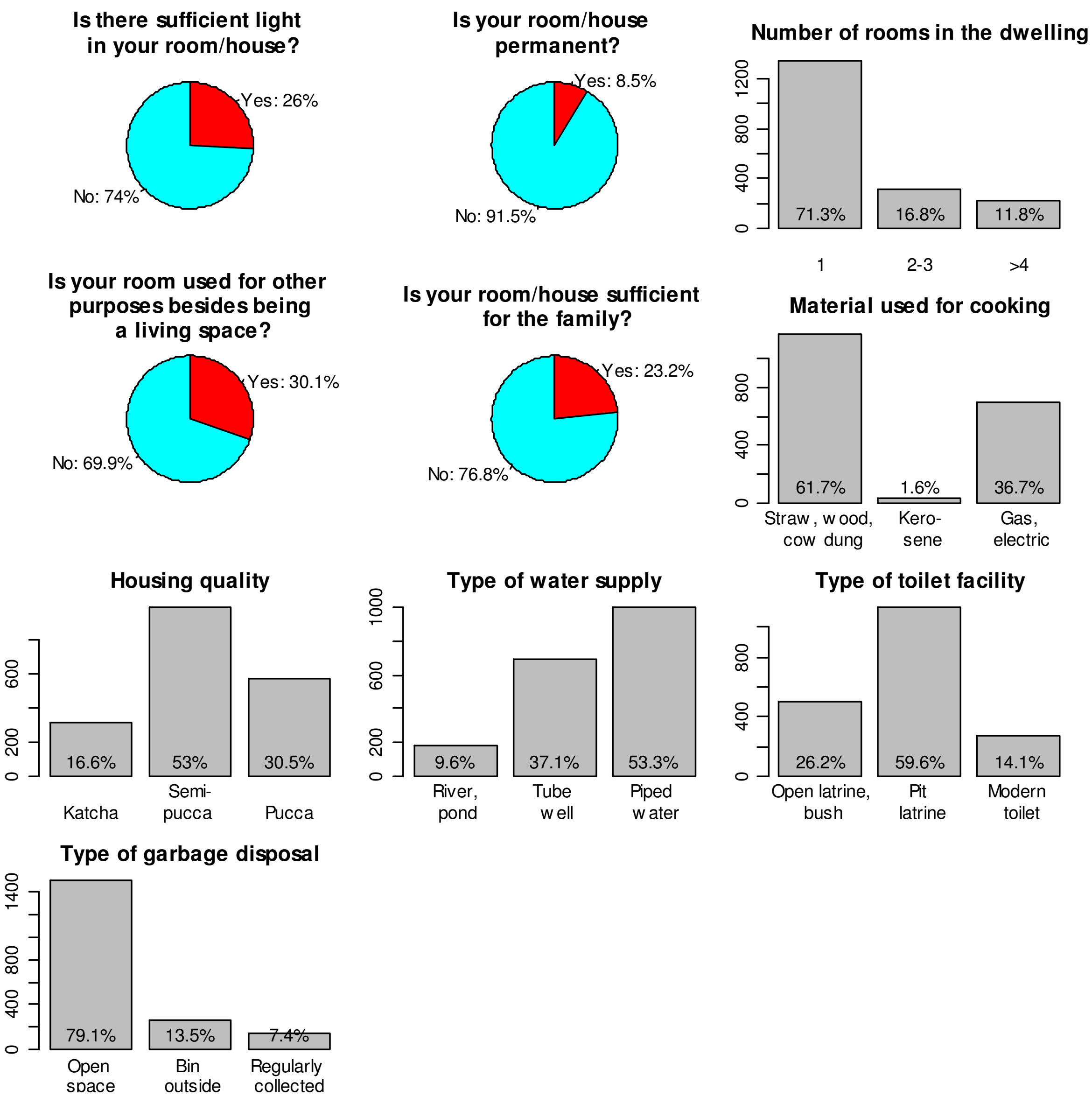


Figure IV-4: Descriptive statistics for socio-physical environmental variables.

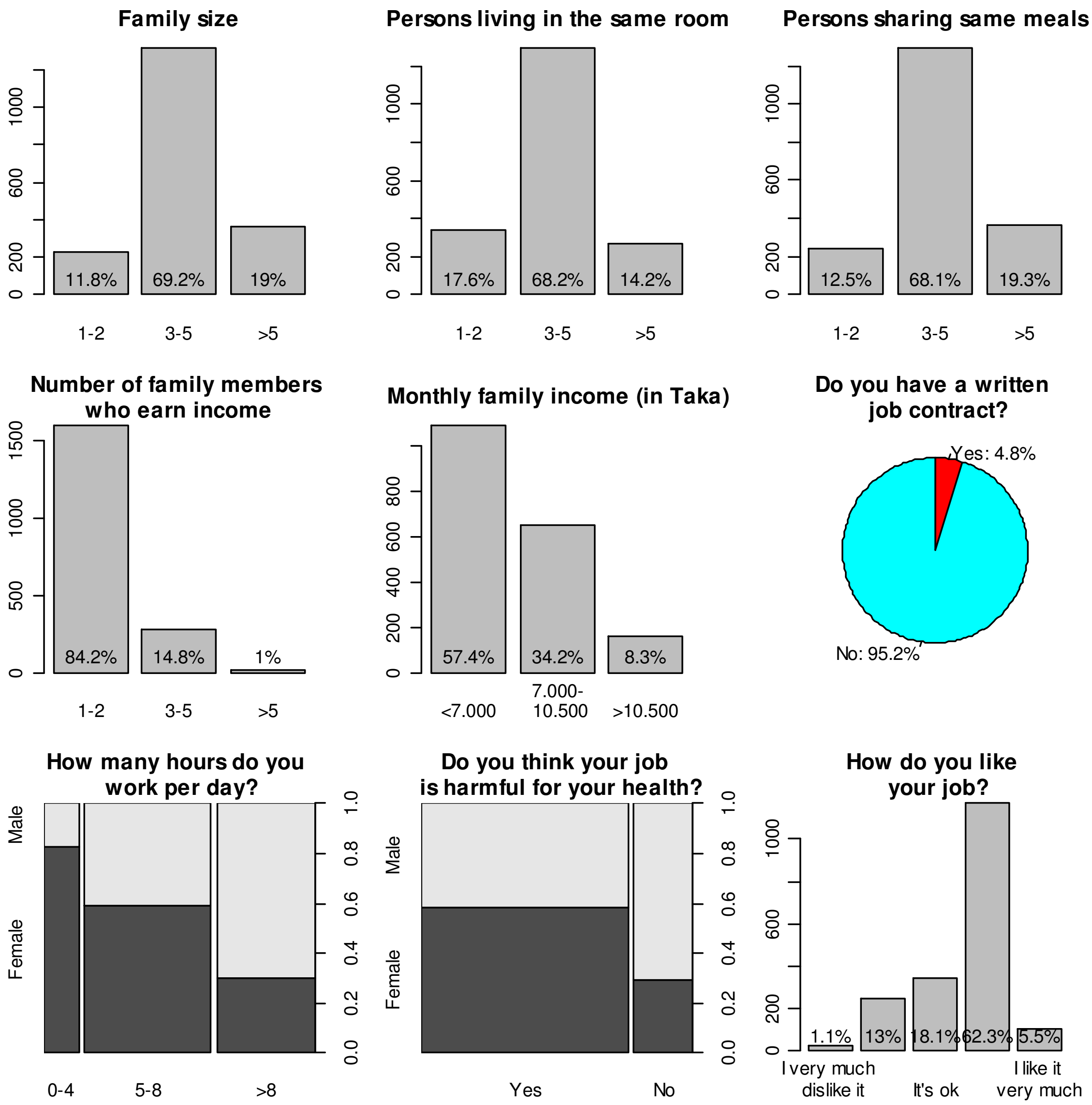


Figure IV-5: Socio-economic conditions of slum households in Dhaka.

3.2 Individual level

Health knowledge and behaviour

Descriptive statistics about the awareness of health risks are given in Figure IV-6. The majority of the respondents were aware of environmental health threats. They knew that polluted water and open garbage disposal in the neighbourhood could spread disease and may increase the risk of poor health. Furthermore, nearly all respondents were convinced that air pollution is bad for one's health. Nearly all respondents used a bed net.

The awareness that a healthy lifestyle could support one's health was also shared by the majority of the respondents. Physical exercise was considered to have a positive effect on well-being, whereas smoking was thought to have a negative effect on one's personal health. However, most of the respondents reported that at least one or two of their family members smoke (cf. Figure IV-7). The cigarette smokers were mostly men. When smoking, men were also more likely to smoke inside the room.

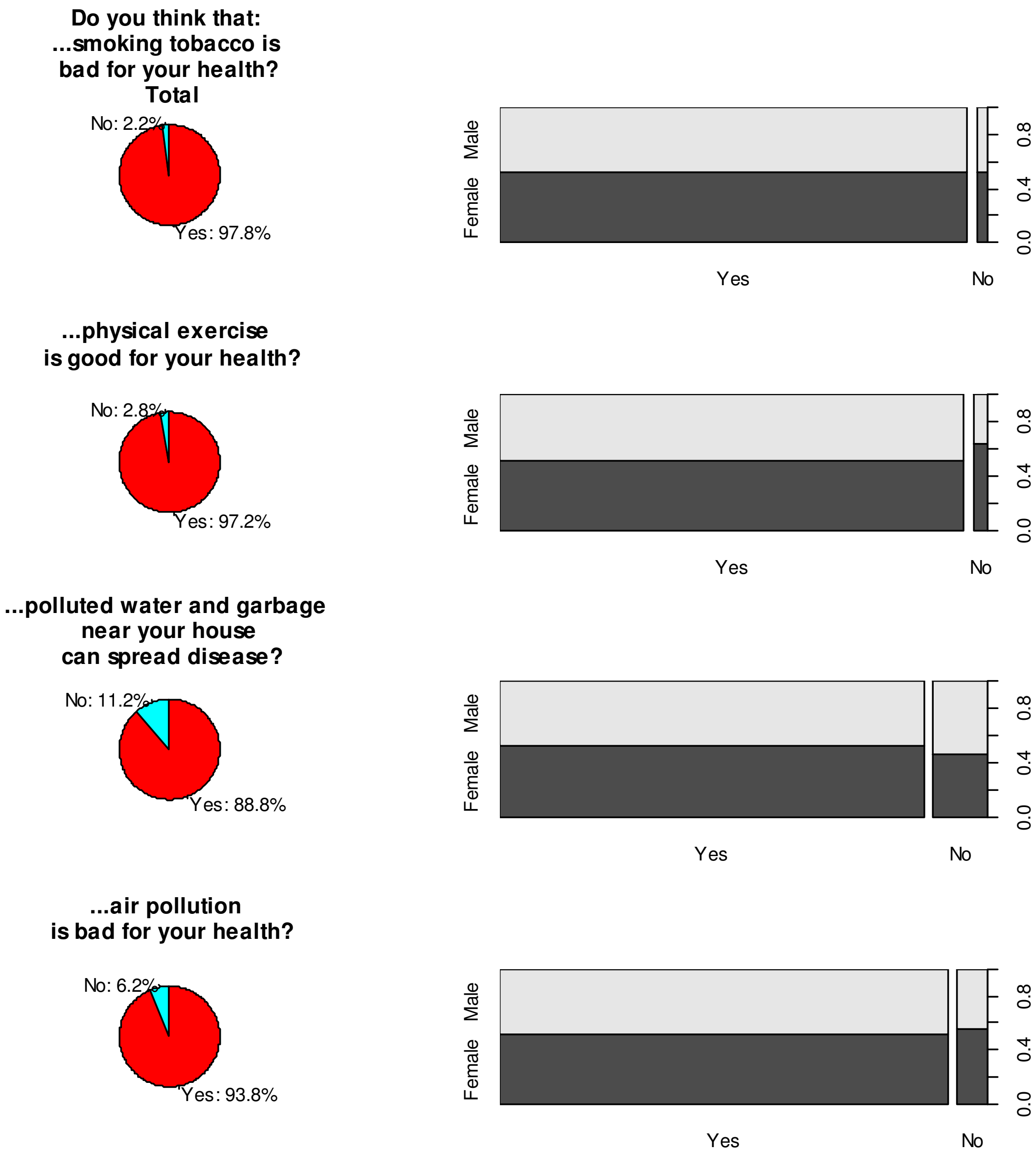


Figure IV-6: Descriptive statistics for health knowledge of respondents.

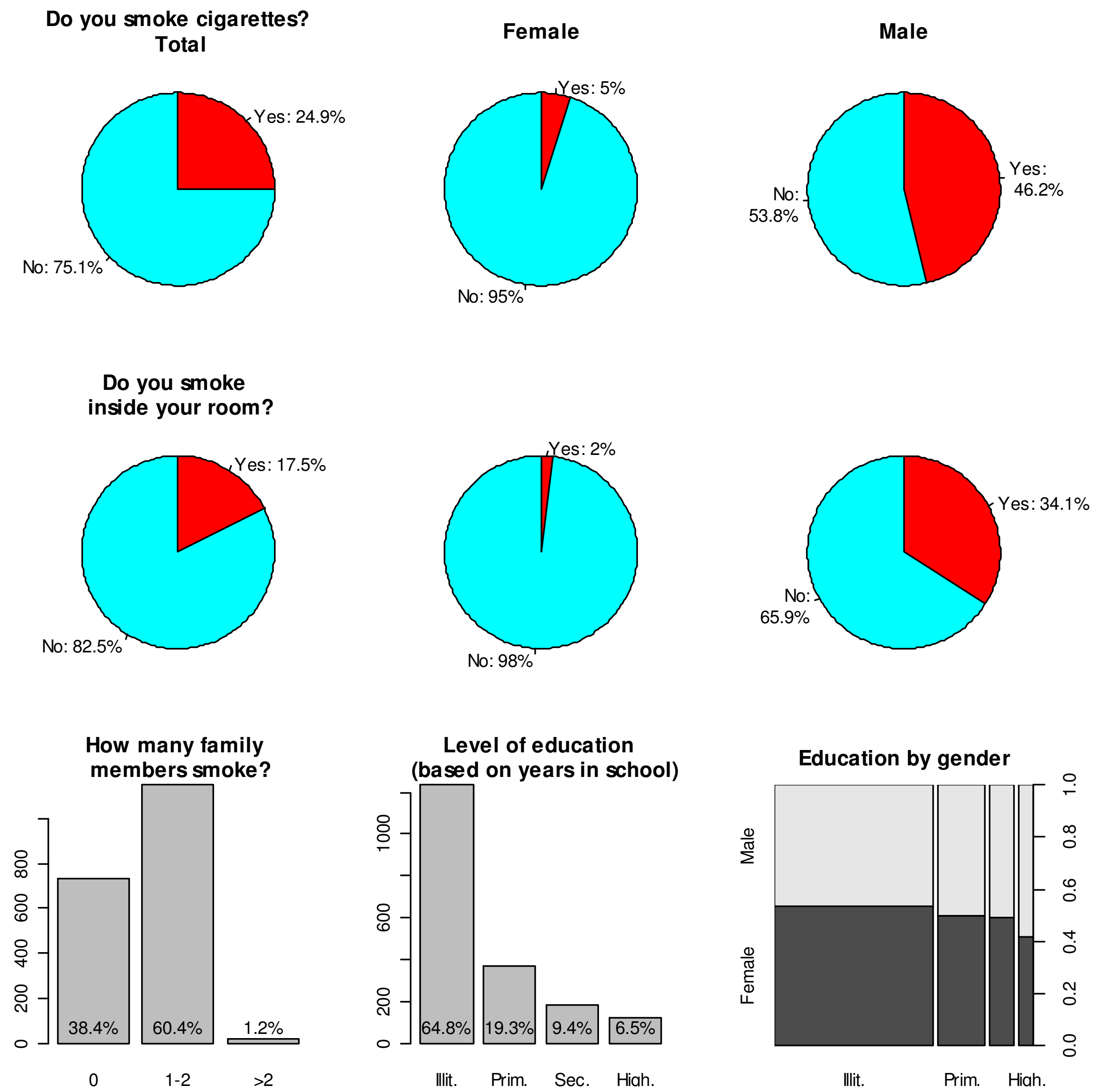


Figure IV-7: Descriptive statistics for smoking behaviour of respondents and levels of education.

Personal characteristics

The respondents were mostly females (52%) and fewer males (48%). Socio-demographic conditions of the respondents are given in Figure IV-7 and IV-8. Most of the respondents were illiterate, however within the higher education group there were fewer women than men. The average age of the respondents was 34.6 years. The average age of males (37.8 years) was higher than that of females (31.6 years). Most of the respondents were married. A slightly higher proportion of women were engaged in community activities than men. Most of the respondents were born in a village and were migrants to Dhaka.

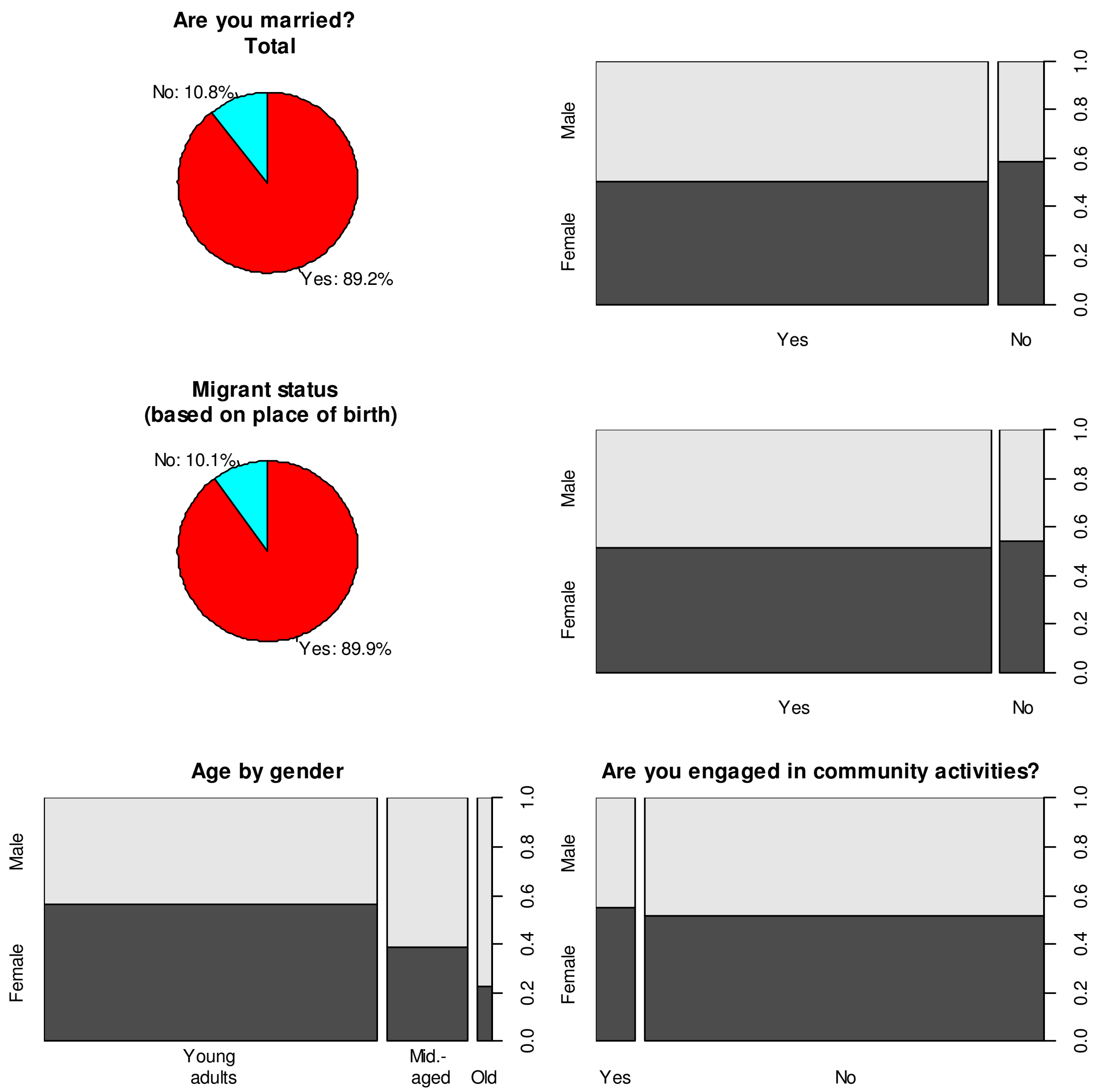


Figure IV-8: Socio-demographic characteristics of slum dwellers.

4 Health outcomes

Good mental health (WHO-5 scores ≥13) was found in 20% of the total population sample (n= 1644); 21% of females and 25% of males reported good mental health (cf. Figure IV-9). Slum dwellers rated their health mainly as “so-so” (55%), whereas 9% of the females and 8% of the males reported poor health status. Furthermore, 78% of the females and 76% of the males reported that they had a disease in the three months preceding the survey.

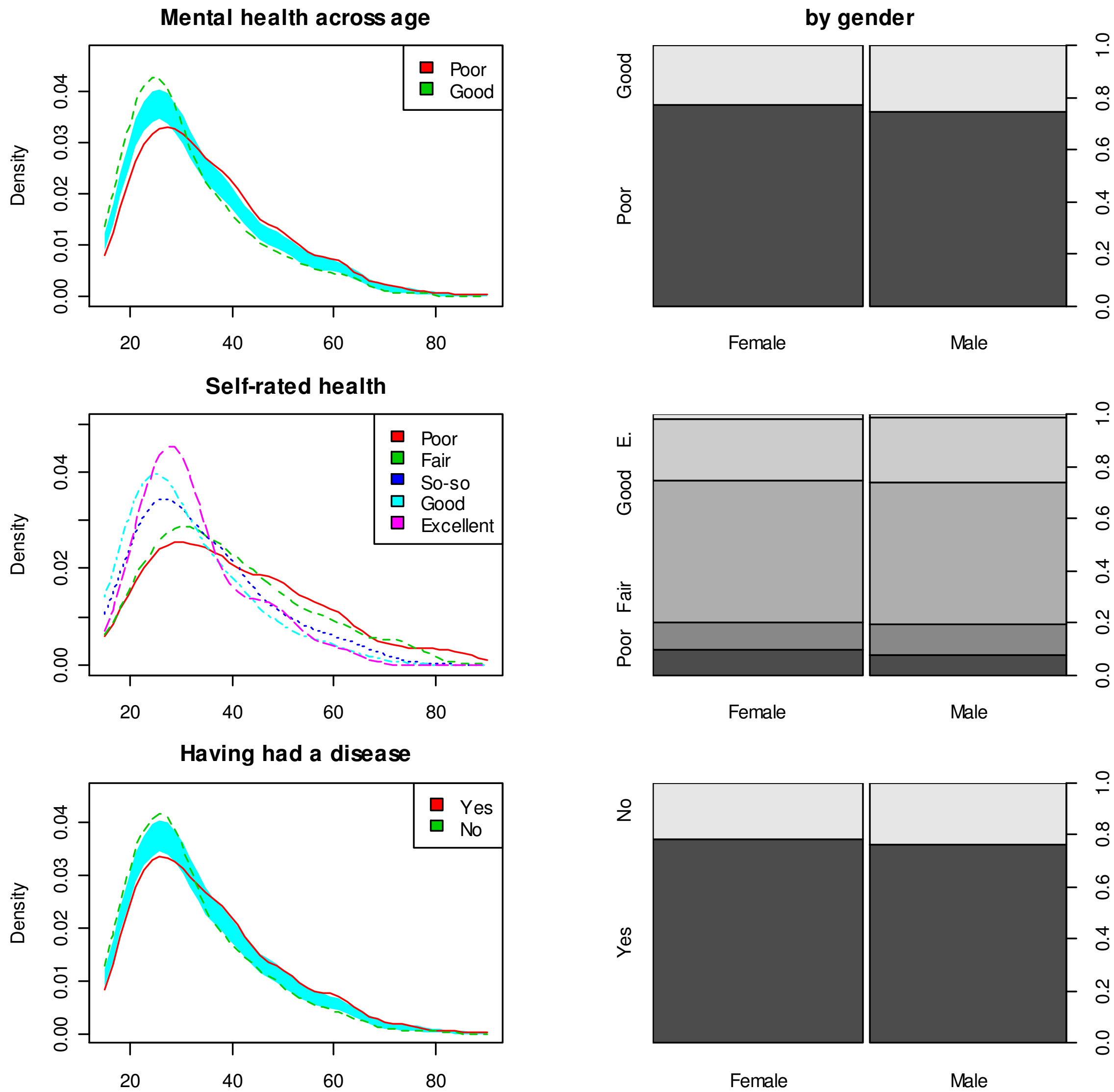


Figure IV-9: Descriptive statistics for health outcomes used in the studies. For the density plots (left), a bootstrap hypothesis test of equality was assessed with the mean of the normal optimal values for the different groups (Bowman and Azzalini 1997). Health outcomes differed significantly ($p<0.05$). The reference band for the hypothesis test is only given in cyan where two groups are compared (e.g., poor and good mental health).

Chapter V:
Mental health in the slums of Dhaka – a geo-epidemiological study

Taken from:

Gruebner, O., Khan, M.M., Lautenbach, S., Müller, D., Krämer, A., Lakes, T., & Hostert, P. (submitted). **Mental health in the slums of Dhaka – A geo-epidemiological study.** *BMC Public Health.*

1 Abstract

Background

Urban health and the quality of urban life are of global concern because the majority of the world's population live in urban areas, mainly in the global south. Although mental health problems (e.g., depression) in developing countries are highly prevalent, such issues are not yet adequately addressed in the rapidly urbanising megacities of these countries, where a growing number of residents live in slums. Little is known about the spectrum and burden of mental health problems in urban slums. Using a geo-epidemiological approach, the present study identified factors that contribute to mental health in the slums of Dhaka, which currently accommodates an estimated population of more than 14 million, including 3.4 million slum dwellers.

Methods

The baseline data from a cohort study conducted in early 2009 in nine slums of Dhaka were used. Data were collected from 1,938 adults (≥15 years). All respondents were geographically marked based on their households using global positioning systems (GPS). Very high-resolution land cover information was processed in a Geographic Information System (GIS) to obtain additional exposure information. We used a principal component analysis to reduce the socio-physical explanatory variables to a smaller set of uncorrelated linear combinations of variables called principal components. We then regressed these principal components on the WHO-5 Well-being Index that was used as a proxy for self-rated mental health.

Results

Mental health was significantly associated with various factors such as selected features of the natural environment, flood non-affectedness, sanitation, and housing quality, sufficiency and durability. We further identified associations with population density, job satisfaction, and income generation while adjusting for individual factors such as age, gender, diseases, health knowledge and migration.

Conclusions

Factors determining mental health were related to the socio-physical environment and individual-level characteristics. Given that mental health conditions could elevate the risk for group I, II, and III diseases, our study may provide crucial information for developing better health care and disease prevention programmes in Dhaka slums and other comparable settings.

The lack of data on the burden of disease morbidity and mental health status in slums hampers the efficient allocation of health care initiatives and the provision of appropriate disease prevention services (Riley et al. 2007). Given that mental disorders elevate the risk for communicable (i.e., group I diseases) and non-communicable diseases (group II), and contribute to injuries (group III) (Prince et al. 2007), assessing the factors that describe the mental health of poor populations residing in urban slums is urgently needed.

In this paper, we applied a geo-epidemiological approach combining very high-resolution land cover information with geo-referenced survey data for obtaining exposure information. We aimed to identify factors that contribute to mental health among slum residents in Dhaka. We focussed exclusively on slum dwellers and considered three different levels: the neighbourhood, the household, and the individual. We hypothesised that the mental health of slum dwellers is associated with the social and physical environment even after adjusting the impact of personal factors such as age, gender and diseases.

2 Methods

2.1 Health outcomes

We used the WHO-5 Well-being Index as the primary outcome for mental health. Additionally, we used the variable "self-rated health" as a second and having had a disease in the three months preceding the survey as a third measure for health status.

2.2 Geoprocessing

We used data from Quickbird satellite imagery from January 22nd, 2006 to estimate land cover properties. The overall land cover classification accuracy for this data was 91.8% with 0.97% for vegetation and 0.90% for water. For more details on the land cover classification, please refer to Kabir et al. (2010) who used the same Quickbird data to calculate bright roof tops for solar PV applications in Dhaka. Vegetation and water coverage in 100-m buffers around GPS-located households from the cohort study were calculated using geoprocessing applied on the extracted land cover classes. In addition, distances from the survey-household coordinates to the nearest river, street and park gathered from GoogleMaps^{TM} were calculated in a GIS (Geographic Information System).

Figure V-1 presents a flowchart of our geo-epidemiological approach. All geoprocessing steps were done in ArcGIS version 9.3.1 (ESRI 2010).

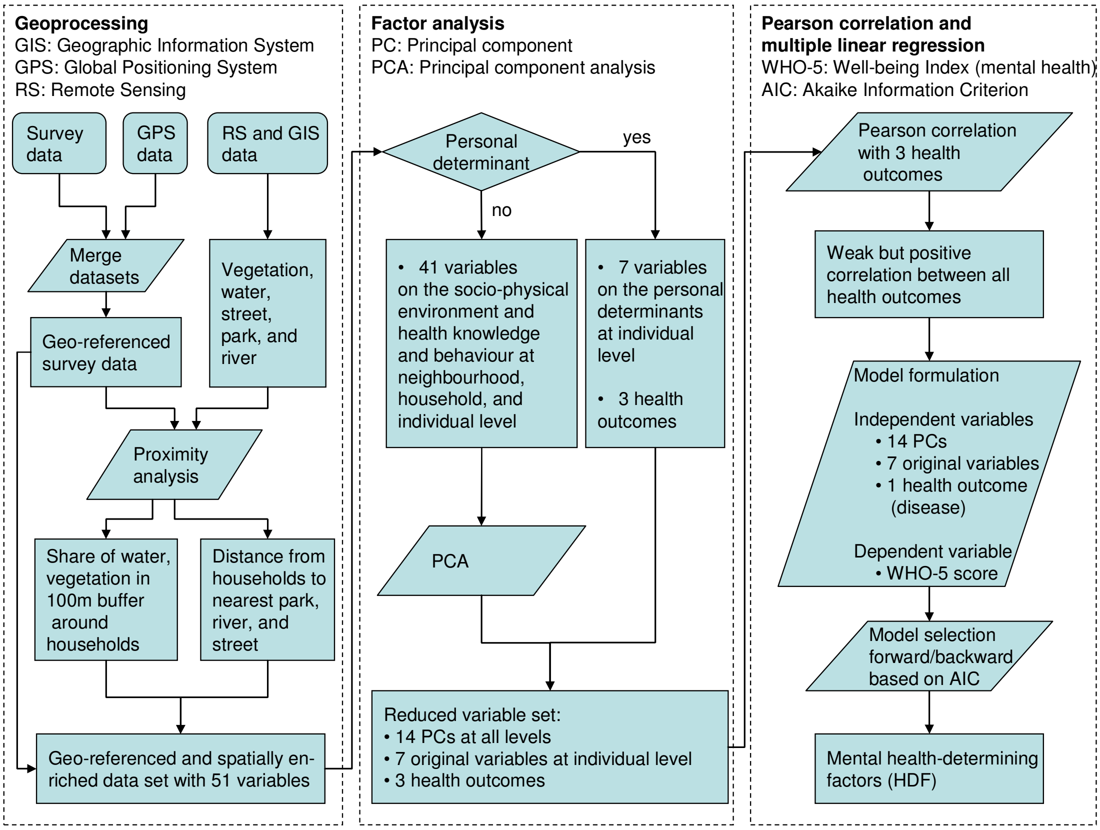


Figure V-1: Geo-epidemiological approach used for this study. Parallelograms stand for geoprocessing or statistical processes, rhombuses for selection criteria and rectangles for outcomes. Note that levels were used only for conceptualising the socio-physical environment. All of the variables were available on the individual level (i.e., separately for each respondent). To prevent information loss, no aggregation to higher levels was performed.

2.3 Principal component analysis

We used principal component analysis (PCA) in SPSS (Version 17) to reduce our variable set given in Table IV-2 to a smaller number of uncorrelated linear combinations of variables that contain most of the variance (Jolliffe 2002). The principal components were based on the correlation matrix. We extracted the factors with a varimax-rotated solution with a Kaiser normalisation based on eigenvalues greater than one (Kaiser 1960; Jolliffe 2002). The variables for age, gender, education, marital status, migration background, using a bed net, and community membership were conceptualised as personal characteristics and were used directly in the multivariable linear regression model. Hence, they were not included in the PCA. Health outcomes were also not included in PCA.

2.4 Multivariable linear regression analysis

Associations between the set of independent variables (subsequently termed mental health-determining factors or HDFs) and mental health (WHO-5) were studied using generalised linear regression models with a negative binomial distribution.

We included all HDFs found through the PCA. We also included the original variables for the individual level (for details, refer to Chapter IV). Multivariable regression analysis was applied using the function "glm.nb" available within the MASS packet in the statistical programming environment R (R Development Core Team 2010). We used the "stepAIC" algorithm with both backward and forward selection according to the Akaike Information Criterion (Venables and Ripley 2002) in order to find the best model for describing mental health by the explanatory variables.

3 Results

3.1 Geo-epidemiological variables

We generated five geo-epidemiological variables through geo-processing in the GIS, which we subsequently used in the principal components analysis. See Figure V-2 for descriptive statistics on geo-epidemiological variables.

Euclidean distances to the nearest major river, street and designated park areas were measured and categorised according to whether they were reachable within a walking distance of 1 km. Rivers were found to be within walking distance for more than three-quarters of the households, and the nearest major street was also found to be within walking distance for 90% of the slum dwellers. Only the urban park areas were found to be beyond walking distances for the majority (90%) of the investigated households. We also found that the area within 100 metres around the houses of about 60% of the slum dwellers contained more than 10% green vegetation patches. In addition, 90% of the households were in neighbourhoods with less than 10% surface water, including rivers, lakes, and ponds.

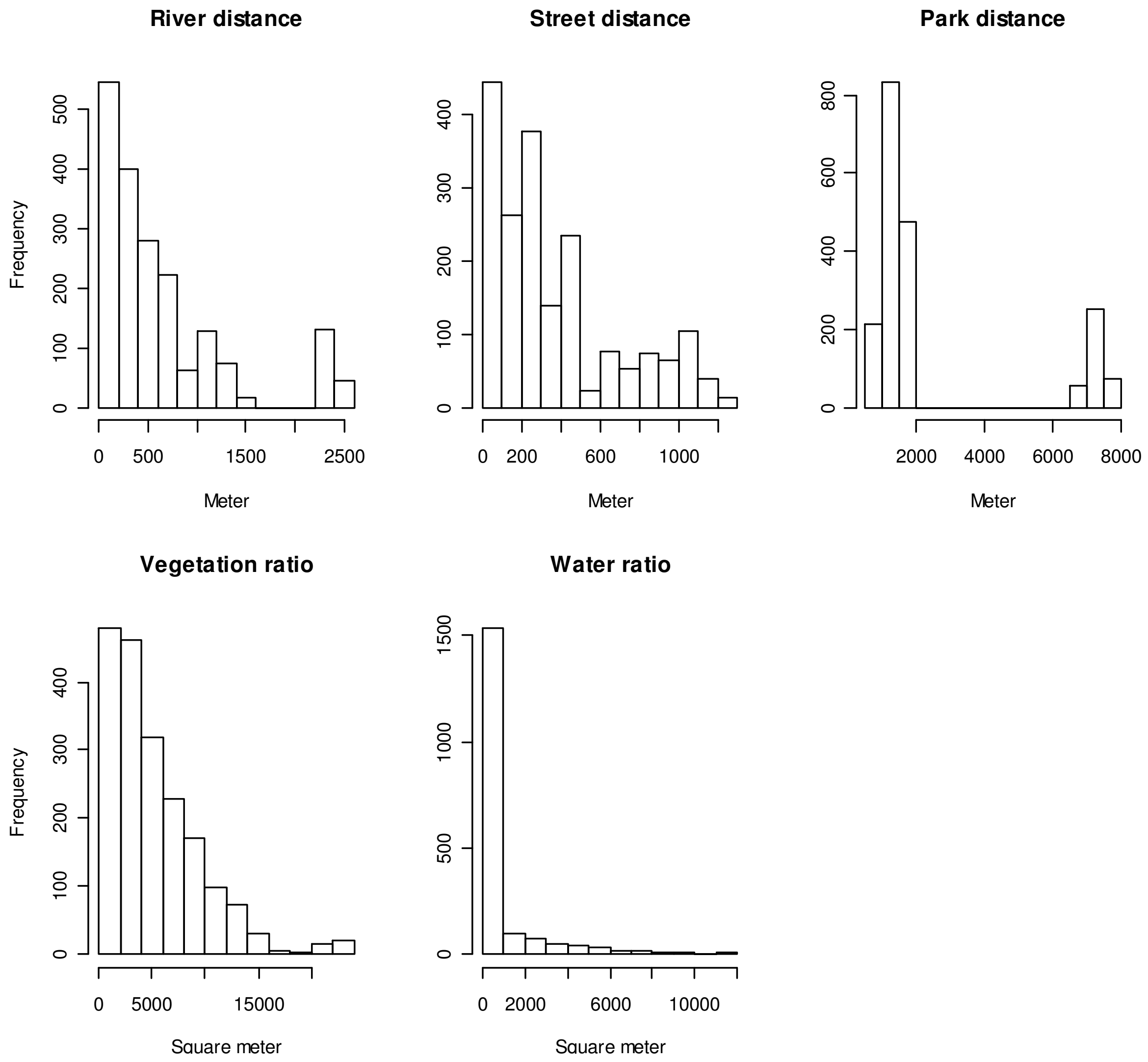


Figure V-2: Descriptive statistics for geo-epidemiological variables gained through geoprocessing.

3.2 Principal components

We identified 14 principal components (PCs) from the 41 variables, including the geo-epidemiological variables, which we subsequently used as covariates in the multivariable linear regression analysis. The PCs represent the socio-physical environment and individual health knowledge and behaviour; they explained 59.5% of the variance in the data, ranging from 6.3% (housing quality) to 3.4% (personal health knowledge) (cf. Table V-1 and Figure V-3).

Table V-1: Explanatory variables used for this study. They were obtained through the prior principal components analysis. In the table, we report the name of each health-determining factor (HDF) and, in brackets, the explained variance. The original variables that were found to be correlated with these HDF are also displayed, with Pearson correlation coefficients in brackets.

Level		Health-determining factor (explained variance)	Original variables (Pearson correlation coefficients)
Neighbourhood	**Physical environment**	Natural environment (4.3%)	○ Vegetation ratio 100 m around household (0.8) ○ Surface water ratio 100 m around household (-0.6) ○ Distance to nearest street (0.7)
		Flood non-affectedness (4.1%)	○ Distance to nearest river (0.5) ○ Is your area flood-affected? (0.7) ○ Does your area have a proper drainage system? (0.7)
Household	**Physical environment**	Housing quality (6.3%)	○ Monthly rent for the house (0.6) ○ Family has household item: gas burner (0.8) ○ Cooking material (0.9) ○ Housing construction material (0.5)
		Basic services (4.7%)	○ Distance to nearest park (-0.8) ○ Distance to nearest river (0.5) ○ Family has household item: electric fan (0.6) ○ Type of water supply (0.5)
		Sanitation (3.6%)	○ Type of toilet facility (0.7) ○ Type of garbage disposal (0.6)
		Housing sufficiency (3.6%)	○ Light sufficiency in the house (0.6) ○ Room is used also for purposes other than living (0.7) ○ Room is sufficient for family (0.5)
		Housing durability (3.5%)	○ Family has household item: refrigerator (0.7) ○ Is your house provisional or permanent? (0.8)
	Socio-economic environment	Household wealth (4.3%)	○ Family has household item: radio (0.6), TV (0.6), tape/CD/VCD (0.7) ○ How many rooms do you have? (0.5)
		Job satisfaction (4%)	○ Working hours per day (-0.4) ○ Do you think your job is harmful for your health? (0.8) ○ Do you like your job? (0.7)
		Income generation (3.7%)	○ Do you have a job contract? (0.4) ○ Family members earning income (0.7) ○ Monthly family income (0.7) ○ Working hours per day (0.2)
	Social environment	Population density (5.2%)	○ Family size (0.8) ○ Persons sharing same meals (0.7) ○ Persons living in the same room (0.7)
Individual		Smoking behaviour (4.8%)	○ Do you smoke cigarettes? (0.8) ○ Do you smoke inside your room? (0.8) ○ How many family members smoke? (-0.7)

Environmental health knowledge (3.9%)	Do you think that: o …polluted/logged water/garbage near the house spread disease and increase the risk of poor health? (0.8) o …air pollution is bad for your health? (0.6)
Personal health knowledge (3.4%)	Do you think that: o …smoking tobacco is bad for your health? (0.7) o …physical exercise is good for your health? (0.7)
Community member	Original variables were used
Using bed net	
Education	
Married	
Migrant	
Age	
Gender	
Disease	

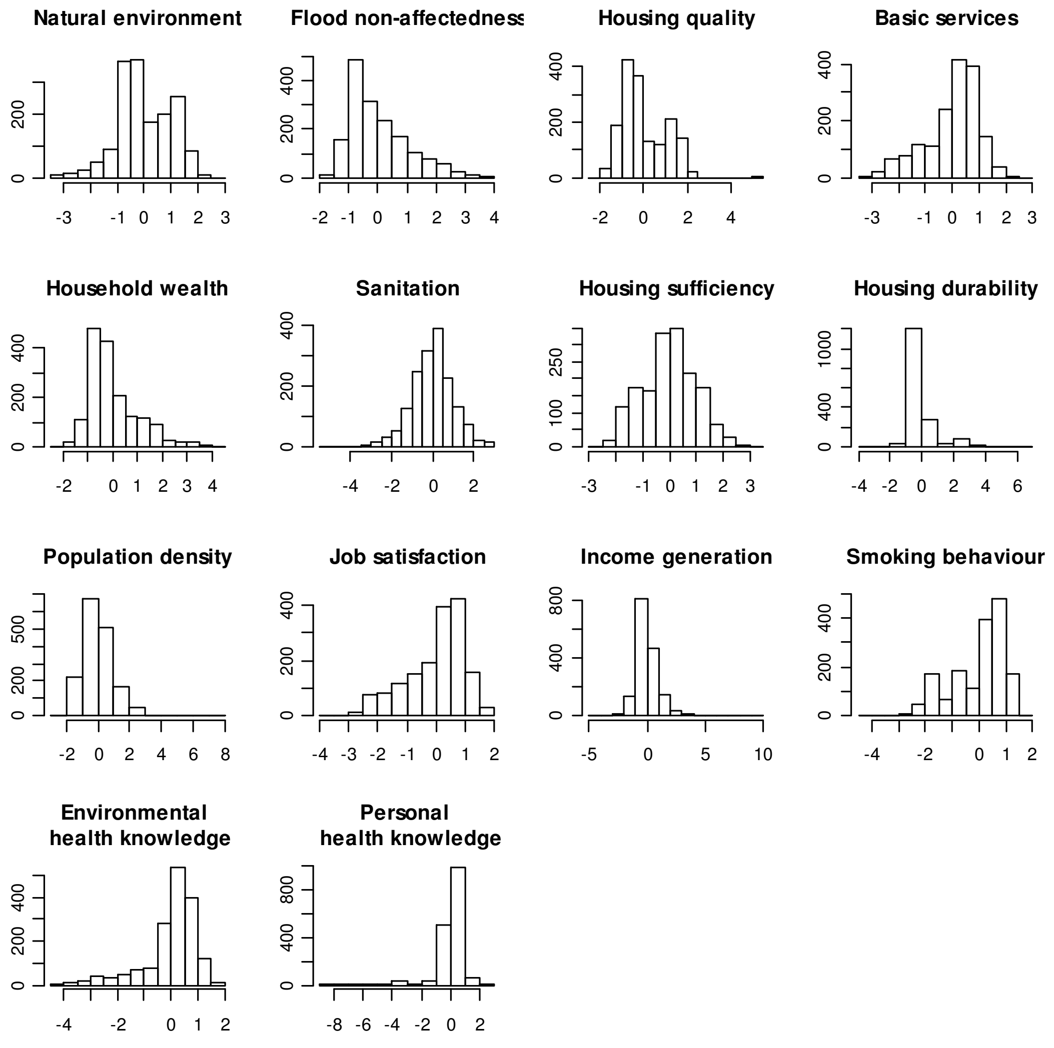


Figure V-3: Descriptive statistics for WHO-5 scores (mental health) and HDF gained by principal component analysis.

3.3 Health outcomes

Good mental health (WHO-5 scores ≥13) was found in 21% of females and in 25% of males (cf. Figure V-4 A). Good mental health was also found in 25% of the poorest (lower household wealth quintile) and 26% of the least poor (upper household wealth quintile) population groups (cf. Figure V-4 B). Slum dwellers rated their health mainly as "so-so" (56%), whereas good or excellent health status was reported by 27% of the poorest and 30% of the least poor population groups.

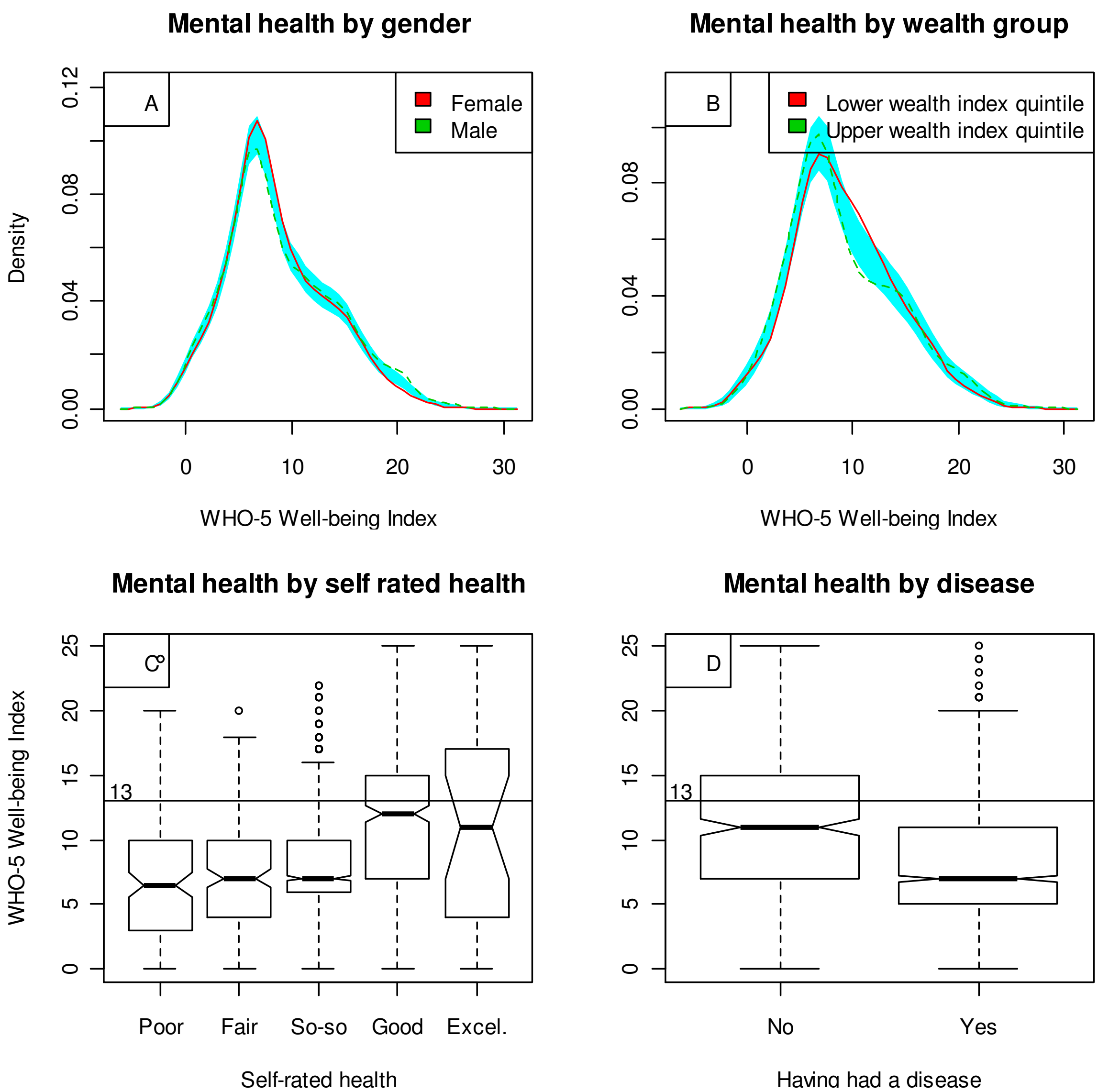


Figure V-4: Descriptive statistics for WHO-5 scores (mental health), self-rated health and diseases. WHO-5 scores of <13 suggest poor mental health and are an indicator for depression. Note that for A and B, a bootstrap hypothesis test of equality between the both groups was applied with gender being equal (p value=0.55) and wealth group being significantly different from each other (p value=0.04), indicated by a reference band in cyan.

We also found that the WHO-5 scores were positively correlated with self-rated health (Pearson correlation coefficient=0.32, p<.001) (cf. Figure V-4 C). Similarly, 78% of the females and 76% of the males reported that they had had a disease in the three months preceding the survey (not shown). The WHO-5 scores were therefore negatively correlated with “having had a disease in the three months preceding the survey” (Pearson correlation coefficient =-0.24, p<.001) (cf. Figure V-4 D).

3.4 Mental health determining factors

We identified several HDFs from the socio-physical environment and found that they had significant associations with mental health (Table V-2). Furthermore, personal determinants like gender, age, and disease were significantly associated with mental health. We found the strongest positive association between mental health and environmental health knowledge while controlling for male gender. Furthermore, mental health was positively associated with lower flood risk (flood non-affectedness), better sanitation, better income generation ability, job satisfaction, and higher quality, sufficiency, and durability of housing. A strong negative association was found for respondents who had suffered from any disease in the three months prior to the survey. Mental health was further found to be negatively associated with age, better personal health knowledge, higher population density, and selected features of the natural environment. However, basic services, household wealth, smoking behaviour, using bed net, marital status, and education were not significantly associated with mental health and were removed from the model. The model could explain 20% of the variance.

Table V-2: Determinants of mental health (WHO-5). A multivariable linear regression model was used assuming a negative-binomial distribution of the target variable, mental health (WHO-5 score). The explanatory variables (HDF) are displayed in the table. A forward/backward model selection approach was used based on AIC. Note that, despite conceptualising the HDF at multiple levels, all analyses were performed at the individual level.

Level		Mental health-determining factor (HDF)	Multivariable linear regression	
			Coefficient	95%CI LL / UL
Neighbourhood Physical environment		Natural environment	-0.06***	-0.08 / -0.03
		Flood non-affectedness	0.06***	0.04 / 0.09
Household	Physical environment	Housing quality	0.03*	0.01 / 0.06
		Basic services	---	---
		Sanitation	0.08***	0.06 / 0.11
		Housing sufficiency	0.07***	0.04 / 0.09
		Housing durability	0.07***	0.05 / 0.09
	Socio-economic Environment	Household wealth	---	---
		Job satisfaction	0.09***	0.06 / 0.11
		Income generation	0.08***	0.06 / 0.11
	Social Environment	Population density	-0.05***	-0.07 / -0.02
Individual		Smoking behaviour	---	---
		Environmental health knowledge	0.11***	0.08 / 0.13
		Personal health knowledge	-0.03*	-0.05 / -0.004
		Community member	0.07.	-0.02 / 0.15
		Using bed net	---	---
		Education	---	---
		Married	---	---
		Migrant	0.06.	-0.02 / 0.15
		Age	-0.01***	-0.01 / -0.004
		Gender:		
		Female	Reference	
		Male	0.11***	0.06 / 0.16
		Having had a disease:		
		No	Reference	
		Yes	-0.22***	-0.28 / -0.16

Significance codes: <0.001 '*', < 0.01 '**', < 0.05 '*', >0.05 '.', not in model '---'**

CI: Confidence interval with LL= Lower limit and UL= Upper limit

4 Discussion

The socio-physical environments of slums are diverse and can compromise or promote health in a variety of ways. We analysed the determinants of mental health status among slum dwellers in Dhaka and hypothesised that mental health is associated with the social and physical environments even after adjusting the impact of personal factors such as age, gender and diseases. We found that mental health conditions were unequally distributed among the population, and younger, male, and more affluent dwellers enjoyed better mental health (cf. Rahman and Barsky 2003; Izutsu et al. 2006; Ompad et al. 2007). Furthermore, physical health conditions were associated with mental health conditions, which is in accordance with Prince et al. (2007). In summary, our study adds evidence regarding factors determining the mental health of slum residents in Dhaka. We believe that these findings apply to comparable settings in other regions as well.

4.1 Individual level associations with mental health

At the individual level, mental health was positively associated with environmental health knowledge, which reflects a person's awareness of environmental threats (i.e., that polluted, stagnant water and garbage near one's house could spread disease and that air pollution increases the risk of poor health). Such knowledge may justify protective measures and eventual adaptation strategies of the local residents. An interesting fact is the observed negative relationship between mental health and personal health knowledge, which reflects a person's awareness of the effects of personal sedentary lifestyles and other activities that can cause poor health, such as smoking or less physical exercise. One explanation for this relationship could be that a higher awareness of health issues might have caused a tendency to be dissatisfied with the overall poor living conditions.

4.2 Mental health and the built environment

Although having measured all variables at the individual level, we conceptualised mental health determining factors (HDF) at different levels for ease of interpretation. Most HDF at the household level, for instance, relate to the built environment. Unfavourable housing quality is thereby assumed to cause poor health by provoking asthma and other respiratory conditions, injuries, or psychological distress or by hindering child development (Vlahov et al. 2007). Good sanitation (i.e., garbage disposal and the quality of the toilet facility) can decrease the risk of infectious diseases and other ailments, such as gastrointestinal diseases or respiratory diseases (Vlahov et al. 2007). In accordance with these relationships, mental health in the slums of Dhaka was positively associated with good sanitation. Furthermore, the quality, sufficiency, and durability of housing were found to be positively associated with mental health. Each of these predictors could capture the socio-economic status (SES) of an individual or household that is well known to be associated with mental health (cf. Galea et al. 2007; Ompad et al. 2007; Aneshensel 2009). These predictors can define the frame of action within which a household can respond to health threats (Villagrán De León 2006; Gruebner et al. 2011b). Hence, these factors could also be conceptualised as belonging to the socio-economic environment. In any case, these factors may shape the intrinsic ability of an individual or household to resist or cope with the impact of a possible physical or social event (Villagrán De León 2006) and were therefore crucial determinants of mental health in our study.

4.3 Mental health and the natural environment

The rapid urban expansion of Dhaka has facilitated a huge loss of prime agricultural areas and wetlands (Griffiths et al. 2010; Byomkesh et al. 2011), which are generally known to provide important provisioning and regulating ecosystem goods and services (ESS)(MA 2005), which support health in a variety of ways (Corvalán et al. 2005). In Dhaka, for instance, water retention areas have been increasingly lost due to the widespread practice of earth in-filling during ground construction. The loss of ESS regulation, combined with poor infrastructural planning, has thus led to deteriorating living conditions and increased environmental risks, particularly the risk of flooding (Caldwell 2004). As slum dwellers in Dhaka are highly vulnerable to flood events (Braun and Aßheuer 2011), it is consequently quite understandable that not being affected by flooding was found to be positively associated with mental health in our study.

Having large areas of vegetation in the nearby neighbourhood often increases the health-related quality of life, for example, by reducing heat stress induced through a local urban heat island effect (Bowler et al. 2010; Burkart et al. 2011; Uejio et al. 2011). Furthermore, urban green and park areas are typically considered to be recreational facilities for urban residents (Galea et al. 2005b; Alberti 2009). In Dhaka's slums, vegetation cover is scarce, and we therefore assumed a strongly positive association between nearby green areas and mental health. However, many of those areas that we had expected to improve living conditions and thus improve mental health turned out to be low-lying and regularly flooded areas. Combined with poor sanitation, open waste water drainage, and garbage disposal, such vegetation patches increase the risk for infectious disease (e.g., diarrhoea or worm infections) (Sclar et al. 2005). Our analysis thus identified ecosystem disservices (Lyytimaki and Sipila 2009) rather than ESS and showed that these areas are also associated with non-infectious diseases, namely, poor mental health.

4.4 Mental health and the socio-economic environment

Our study revealed a positive association of well-being with income generation and job satisfaction, describing the ability to generate income as well as satisfaction and safety at work. More than 80% of Dhaka's adult slum dwellers are engaged in the informal economy, which provides a means of survival for a substantial section of the workforce (Kulke and Staffeld 2009). The informal economy is often associated with unfavourable environments with regard to working and living conditions, pollutants, discrimination, exploitation, income, occupational safety, and legal and social security (Barten et al. 2008; Gruebner et al. 2011b). Against this background, it becomes clear why good income generation and job satisfaction showed up as important predictors for good mental health among Dhaka's slum dwellers.

For mental health, population density was also an important factor in our study. We hypothesised that in the slums of Dhaka, crowding put enormous stress on residents with consequent implications for mental health, possibly due to a lack of privacy. Other studies showed that social norms in densely populated urban areas may further support individual or group behaviours that affect health outcomes (e.g., smoking, diet, exercise, or sexual behaviour) (Galea et al. 2005b).

5 Conclusions

From this study, we were able to describe the status of mental health in Dhaka's slums. The most important factors that determined mental health were job satisfaction, income generation ability, population density, flood non-affectedness, sanitation, quality, sufficiency and durability of the house, and selected properties of the natural environment. Individual-level characteristics such as diseases, gender, and health knowledge were important mental health determinants. Given that mental health conditions could elevate the risk for group I (communicable disease), group II (non-communicable disease), and group III diseases (injuries), our study provided crucial information for developing better health care and disease prevention programmes in Dhaka's slums and comparable settings worldwide.

Chapter VI: A spatial epidemiological analysis of self-rated mental health in the slums of Dhaka

Taken from:

Gruebner O, Khan MMH, Lautenbach S, Müller D, Krämer A, Lakes T, Hostert P: **A spatial epidemiological analysis of self-rated mental health in the slums of Dhaka.** *International Journal of Health Geographics* 2011, **10:**36.

1 Abstract

Background

The deprived physical environments present in slums are well-known to have adverse health effects on their residents. However, little is known about the health effects of the social environments in slums. Moreover, neighbourhood quantitative spatial analyses of the mental health status of slum residents are still rare. The aim of this paper is to study self-rated mental health data in several slums of Dhaka, Bangladesh, by accounting for neighbourhood social and physical associations using spatial statistics. We hypothesised that mental health would show a significant spatial pattern in different population groups, and that the spatial patterns would relate to spatially-correlated health-determining factors (HDF).

Methods

We applied a spatial epidemiological approach, including non-spatial ANOVA/ANCOVA, as well as global and local univariate and bivariate Moran's *I* statistics. The WHO-5 Well-being Index was used as a measure of self-rated mental health.

Results

We found that poor mental health (WHO-5 scores <13) among the adult population (age ≥15) was prevalent in all slum settlements. We detected spatially autocorrelated WHO-5 scores (i.e., spatial clusters of poor and good mental health among different population groups). Further, we detected spatial associations between mental health and housing quality, sanitation, income generation, environmental health knowledge, education, age, gender, flood non-affectedness, and selected properties of the natural environment.

Conclusions

Spatial patterns of mental health were detected and could be partly explained by spatially correlated HDF. We thereby showed that the socio-physical neighbourhood was significantly associated with health status, i.e., mental health at one location was spatially dependent on the mental health and HDF prevalent at neighbouring locations. Furthermore, the spatial patterns point to severe health disparities both within and between the slums. In addition to examining health outcomes, the methodology used here is also applicable to residuals of regression models, such as helping to avoid violating the assumption of data independence that underlies many statistical approaches. We assume that similar spatial structures can be found in other studies focussing on neighbourhood effects on health, and therefore argue for a more widespread incorporation of spatial statistics in epidemiological studies.

To our knowledge, no previous study has analysed (i) the associations of neighbourhood socio-physical characteristics with mental health, and (ii) the spatial variation of mental health in urban slums of developing countries. Therefore, we aimed to fill these gaps by investigating mental well-being in selected slums of Dhaka.

A spatial approach to mental health with a focus on spatial structures and autocorrelation of the data prevents a violation of the assumption of data independence, biased coefficient estimates, and p-values biased towards rejecting the null-hypothesis. Furthermore, a spatial approach to epidemiological data leads to the spatial estimation and presentation of health outcomes with the aim of assessing health inequalities, generating hypotheses, and estimating spatial variability in the underlying risks for poor health (Elliott et al. 2006). Spatial epidemiological analysis also enhances well-established techniques such as regression analysis by explicitly addressing autocorrelation. In recent years, spatial statistics have been increasingly used for quantifying and assessing variations in health status in a variety of studies. For example, Demirel et al. (2009) used a spatial autocorrelation analysis to identify locations with high disease rates in Turkey; Pouliou and Elliott (2009) detected spatial clusters of overweight and obese populations in Canada; and Sugumaran et al. (2009) used the Anselin Local Moran's I statistic to uncover spatial clusters of human West Nile virus incidence at the county level in the continental United States.

The goal of this study was to investigate the spatial variability of self-rated mental health status for different population groups in several slums of Dhaka, focussing on the individual, household, and neighbourhood levels. We investigated the hypotheses that mental health shows a significant spatial pattern (e.g., spatial clustering) for different population groups, and that the spatial patterns relate to spatially-correlated health-determining factors (HDF), for example, housing quality or income generation ability.

This study dealt not only with new research questions that are very important from a public health point of view, but also combined two well-established methods from two different disciplines. Moreover, we could generalise our findings in similar settings of developing countries. Briefly, our spatial epidemiological approach will enhance our understanding of specific factors contributing to the health of slum residents.

2 Methods

2.1 Variables used in the study

Similar to Chapter V, we used the WHO-5 Well-being Index as the primary outcome for mental health. Additionally, we used the variable "self rated health" as a second and having had a disease in the three months preceding the survey as a third measure for health status.

The 21 HDF found in Chapter V were taken as explanatory variables for this study. Please refer to Table V-1 for details on the HDF.

2.2 Spatial statistics for epidemiological studies

We used a spatial epidemiological approach to detect and explain spatial clusters of WHO-5 scores of urban slum residents (cf. Figure VI-1).

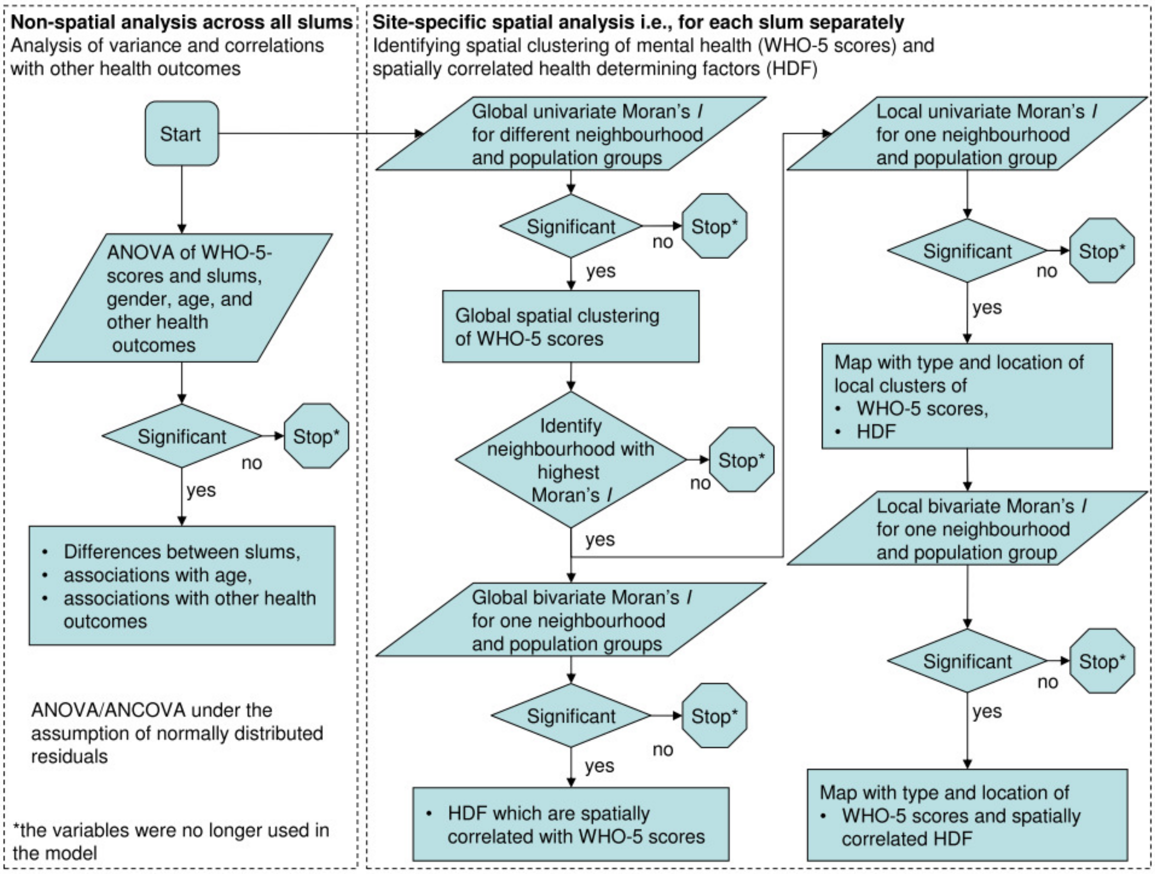


Figure VI-1: Spatial epidemiological approach used for this study. Parallelograms stand for statistical processes, rhombuses for selection criteria and rectangles for outcomes.

We started with a (non-spatial) analysis of variance/covariance (ANOVA/ANCOVA) across all slums to identify differences between the slums and to find correlations of WHO-5 scores with age, gender, and other self-rated health outcomes. All subsequent spatial analyses were performed for each slum separately. We focussed on adult slum residents (age ≥15 years) and separated the sampled population in two ways. For the first, we separated the sample population into female and male groups, and for the second, we separated sampled slum residents by age – young adults (15-44 years), middle-aged adults (45-64 years), and older adults (65 and more years) – classified according to the WHO (WHO 1977). In the slum-specific spatial analysis, we dropped the older-adult age group because of its small sample size.

Spatial autocorrelation analysis was applied to summarise the degree to which persons with a similar health status tend to occur next to each other (i.e., form spatial clusters) (Waller and Gotway 2004). We therefore concentrated on global clustering rather than on globally-dispersed patterns. Multivariable spatial correlation analysis was used to gain information on the extent to which values for the well-being of one person (zf) observed at a given location show a systematic (more than likely under spatial randomness) association with another variable (zg) observed at the "neighbouring" locations. This multivariable spatial correlation can be considered in addition to or instead of the usual (non-spatial) correlation between two variables at the same location (Anselin et al. 2002).

Spatial autocorrelation statistics depend on the definition of neighbourhood relationships through which the spatial configuration of the sampled subpopulation was defined prior to analysis. Because they can influence the results (Schabenberger and Gotway 2005), we explored various neighbourhood definitions. First, we used 30-, 60- and 90-meter fixed-band definitions, which treat every observation point inside that search radius as a neighbour. Second, we used the k-neighbour approach, which treats the nearest k observations as neighbours. We used k values of 3, 5, and 10. For both approaches, we used a binary weight matrix to assign weights to the neighbours. This binary weight matrix assigns a weight of unity for neighbours and zero for non-neighbours. The spatial patterns were investigated by global measures that allowed for special clustering tests. For example, in cases of positive spatial autocorrelation, spatially clustered patterns point to the attraction and prevalence of either poor or good well-being. Local indicators of spatial association were applied to indicate the type (e.g., well-being or housing quality, described as either poor or good) and locations of clusters within the settlements (Anselin 1995). All spatial analyses were performed in GeoDa (Anselin 2004).

2.3 Global univariate spatial autocorrelation

We applied Moran's *I* (Moran 1948, 1950) to account for the global spatial autocorrelation of similar and dissimilar WHO-5 scores of the nine slums of Dhaka. For the Moran's *I* statistic, the sum of covariations between the sites for the distance d(i,j) was divided by the overall number of sites W(di,j) within the distance class d(i,j). Thus, the spatial autocorrelation coefficient for a distance class d(i,j) was the average value of spatial autocorrelation at that distance. The Moran's *I* statistic for spatial autocorrelation is defined as follows (Fortin and Dale 2006):

$$I = \frac{n}{S_p} \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}(y_i - \bar{y})(y_j - \bar{y})}{\sum_{i=1}^{n}(y_i - \bar{y})^2}$$

, where (Equation VI-1)

n = the sample size,

$W_{i,j} = \left. \begin{cases} 1 & \text{if sites i, j are neighbours} \\ 0 & \text{otherwise} \end{cases} \right\} =$ row-standardised spatial weights matrix of sites i and j,

Sp $= \sum_{i=1}^{n}\sum_{j=1}^{n} W_{i,j}$ = sum of the number of sampling locations per distance class,

yi = the value at site i (e.g., the WHO-5 scores).

The actual value for Moran's *I* was then compared with the expected value under the assumption of complete randomisation:

E(I) $= -\frac{1}{n-1}$. (Equation VI-2)

Moran's *I* values may range from -1 (dispersed) to +1 (clustered). A Moran's *I* value of 0 suggests complete spatial randomness. To verify that the value of Moran's *I* was significantly different from the expected value, we applied a Monte Carlo randomisation test with 9,999 permutations to achieve highly significant values. Data values were reassigned among the N locations, providing a randomised distribution against which one may judge the observed value. If the observed value of *I* was within the tails of this distribution, there was significant spatial autocorrelation in the data, and the assumption of independence among the observations could be rejected (Cliff and Ord 1981). We then selected for the mental health outcomes for each population group and chose from the nine slums the neighbourhood with the highest Moran's *I* for further bivariate analysis.

2.4 Global bivariate spatial correlation

A bivariate coefficient of spatial correlation between two standardised random variables yk and yo is defined as follows (Wartenberg 1985):

$$m_{ko} = y_k^{'} W^{s} y_o \text{,} \qquad \text{(Equation VI-3)}$$

where $y_k = [x_k - \overline{x_k}] / \delta_k$ and $y_o = [x_o - \overline{x_o}] / \delta_o$ have been standardised such that the mean is zero and the standard deviation equals one, and Ws is a doubly-standardised spatial weight matrix as described above. Multivariable spatial correlation thus focuses on the extent to which values for one variable yk observed at a given location show an association with another variable yo observed at the neighbouring locations (Anselin et al. 2002). This yields the following multivariable counterpart of a Moran-like spatial autocorrelation statistic (Anselin et al. 2002):

$$I_{ko} = \frac{y_k^{'} W y_o}{y_k^{'} y_k} \text{.} \qquad \text{(Equation VI-4)}$$

In this manner, we tested the 21 HDF for spatial correlations with mental health. The significance of this bivariate spatial correlation was assessed, as in the univariate case, by means of a randomisation approach (Anselin 1995).

2.5 Local univariate spatial autocorrelation

We then calculated the local univariate Moran's *I* for WHO-5 scores (and also for HDF) with the identified best neighbourhood (as described above) and respective population group. This allowed us to implement global measures that allow for spatial patterning tests over the whole study region, which test for statistically significant local spatial clusters, including the type and location of these clusters. We concentrated on the Anselin Local Moran's *I* statistic, which is calculated as follows (Anselin 1995; Schabenberger and Gotway 2005):

$$I_i(d) = \frac{(y_i - \overline{y})}{\frac{1}{n}\sum_{i=1}^{n}(y_i - \overline{y})^2} \sum_{i=1}^{n} W_{ij}(d)(y_j - \overline{y}) \text{,} \quad \text{where} \qquad \text{(Equation VI-5)}$$

$W_{i,j}(d)$ is the row-standardised weights matrix given a local neighbourhood search of radius d. The neighbourhood definitions were the same as the global statistics that were applied (i.e., distance and k-neighbours). Assuming complete randomisation, the expected value of $E(I_i)$ is as follows (Fortin and Dale 2006):

$$E(I_i) = \frac{-1}{n-1}\sum_{j=1}^{n} W_{i,j} \quad \text{(Equation VI-6)}$$

Unlike the global Moran's *I*, which has the same expected value for the entire study area, the expected value of local Moran's *I* varies for each sampling location because it is calculated in relation to its particular set of neighbours (Anselin 1995). We calculated the significance of the local Moran's *I* using a randomisation test on the Z-score with 9,999 permutations to achieve highly significant values (Fortin and Dale 2006):

$$Z(I_i) = \frac{[I_i - E(I_i)]}{\sqrt{Var(I_i)}} \quad \text{(Equation VI-7)}$$

Positive spatial autocorrelation occurs when, for example, WHO-5 scores of residents living in one location are surrounded by similar WHO-5 scores of other residents in neighbouring locations (low-low – LL, high-high – HH), thus forming a spatial cluster. Negative spatial autocorrelation appears when high WHO-5 scores are surrounded by low WHO-5 scores (HL) and vice versa (LH) (i.e., when spatial outliers occur) (Anselin 1995). Because Equation VI-3 does not indicate whether a cluster consists of high or low values, the original WHO-5 scores at the sample points are used for classification into LL, HH, LH or HL.

2.6 Local bivariate spatial correlation

In a next step, we calculated the bivariate Moran's *I* for the WHO-5 scores (and also HDF) for the best neighbourhood and population group. Using a similar rationale as in the original development of local indicators of spatial association (LISA) (Anselin 1995), the numerator in Equation VI-4 can be decomposed into the contributions of the individual observations (Anselin et al. 2002). For the traditional univariate Moran's *I* autocorrelation statistic, the local version was termed a local Moran's statistic; its multivariable generalisation can be defined as follows (Anselin et al. 2002):

$$I^i_{ko} = y^i_k \sum_j w_{ij} y^j_o , \quad \text{(Equation VI-8)}$$

using the same notation as before. This statistic provides an indication of the degree of linear association (positive or negative) between the values for one variable yk at a given location i, y_k^i and the average of another variable yo at neighbouring locations j, y_o^j. A greater than indicated similarity under spatial randomness suggests a spatially similar cluster in the two variables. A dissimilarity greater than spatial randomness would imply a strong, local, negative relationship between the two variables (Anselin et al. 2002). The significance of the statistic was assessed by means of the permutation approach.

3 Results

3.1 Variations in well-being among population groups and slums

We found that poor well-being (WHO-5 scores <13) among the adult population (age ≥15 years) was predominant in all slums. Ignoring spatial structures and assuming normally distributed errors, an ANOVA/ANCOVA analysis showed that the WHO-5 scores for males and females did not significantly differ ($p = 0.21$), but age had a significant negative effect (regression coefficient of -0.06 per year of age, $p<0.001$).

WHO-5 scores were positively related with self-rated health (regression coefficient 1.99, $p<.001$) and with “not having had a disease in the three months preceding the survey” (regression coefficient 1.92, $p<0.001$). Furthermore, WHO-5 scores differed significantly between some slums ($p < 0.001$, cf. Figure VI-2 and VI-3). All predictors had low predictive power. Even the model with the slum, age, and gender predictors explained only 14% of the variance.

3.2 Spatial patterns of well-being

We found the strongest global spatial clustering when the three nearest (sampled) neighbours were considered in the analysis (mean distances ranging from 9 to 11.4 meters). Beguntila and Bishil/Sarag were among the settlements with the highest values (cf. Table VI-1). In Beguntila, spatial clustering of well-being was most significant ($p<0.001$) among the young adult age group. Within this age group, good well-being was positively associated with housing quality and male gender. Furthermore, we detected a negative association between well-being and “natural environment” (cf. Table VI-2).

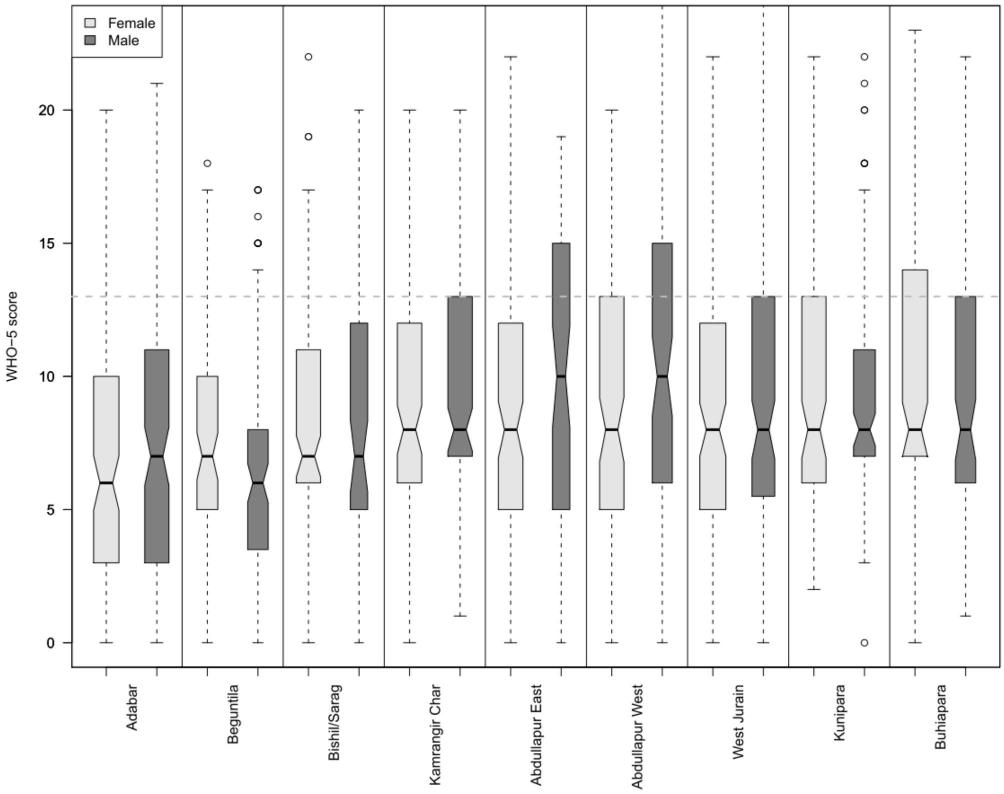


Figure VI-2: Box plot for gender groups across slums.

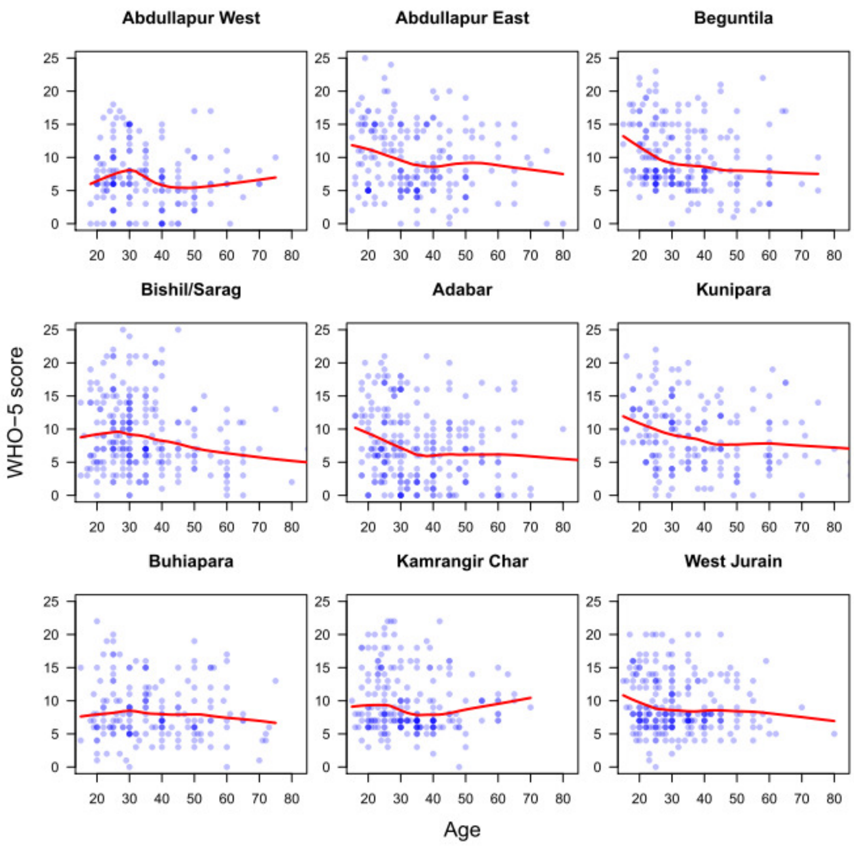


Figure VI-3: Co plot for age across slums.

Table VI-1: Global univariate Moran's *I* values for different neighbourhood relationships. Global Moran's *I* values for those slums and population groups which were significant under a Monte Carlo test with 9,999 permutations (p<0.05). We only report positive Moran values, i.e., those revealing global spatial clustering. For nearest neighbour-based distances, we report in parentheses the average distance-per-slum in metres. Note that the strongest values occur with three nearest neighbours. We thus used this neighbourhood relationship in the subsequent bivariate Moran's *I* analysis.

Neighbour-hood	**Beguntila**	**Bishil/Sarag**				**Abdullapur East**	**Kunipara**	**Adabar**	**Buhiapara**
relation-ship	**Young adults**	**Males**	**Females**	**Young adults**	**Middle aged adults**	**Females**	**Middle aged adults**	**Young adults**	**Total sample**
Nearest neighbours									
3 nn	0.16*	0.19**	0.12*	0.12*	.	.	.	.	.
	(8.5)	*(11.4)*	*(10.8)*	*(9)*					
5 nn	0.16**	0.17**	.	0.1*	.	.	.	.	.
	(10.4)	*(14.7)*		*(11.6)*					
10 nn	0.13**	0.01***	.	.	.	0.06*	0.09*	.	.
	(14.2)	*(20.5)*				(35.2)	(57)		
Fixed distance									
30 m	0.1***	.	.	.	.	.	.	.	.
60 m	0.05**	0.13***	.	0.05**	.	.	.	.	.
90 m	.	0.12***	.	0.03*	0.09**	.	.	0.02*	0.02*

Significance levels: <0.001 '***', < 0.01 '**', < 0.05 '*', >0.05 '.'

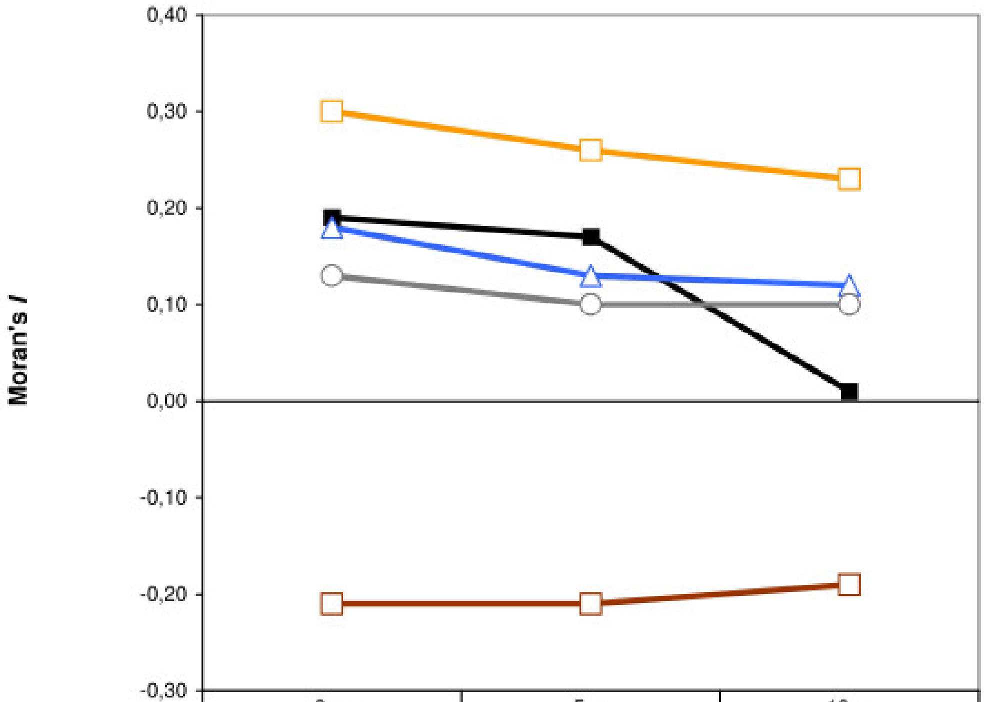
Table VI-2: Global bivariate Moran's *I* values for the three nearest neighbours. The table displays health-determining factors that are significantly (p<0.05) spatially correlated with mental health (WHO-5 scores) of those population groups and slums in which strongest global spatial clustering of WHO-5 scores were found (cf. Table VI-1). Note that the WHO-5 scores among males in Bishil/Sarag are clustered most strongly, and there is a strong spatial correlation with "natural environment" and housing quality in this population group.

Level	**Health Determining Factor**	**Beguntila**	**Bishil/Sarag**		
	WHO-5 scores ~	**Young adults**	**Young adults**	**Females**	**Males**
		n=115	**n=170**	**n=104**	**n=122**
Global univariate Moran's *I* for WHO-5 scores		0.16*	0.12*	0.12*	0.19**
Neighbourhood	"Natural environment"	-0.19***	-0.16***	.	-0.21**
physical environment	Flood non-affectedness	.	0.13**	0.13*	.
Household	Housing quality	0.13*	0.19***	0.14**	0.3***
physical environment	Basic services	.	.	.	.
	Household wealth	.	.	.	.
	Sanitation	.	.	.	0.18***
	Housing sufficiency	.	.	.	.
	Housing durability	.	.	.	.
Household	Population density	.	.	.	.
social and socio-economic environment	Job satisfaction	.	.	.	.
	Income generation	.	0.1*	.	.

Individual	Smoking behaviour	.	.	.	.
	Environmental HK	.	0.09*	.	0.13*
	Personal HK	.	.	.	.
	Community member	.	.	.	.
	Using bed net	.	.	.	.
	Education	.	.	0.11*	.
	Married	.	.	.	.
	Migrant	.	.	.	.
	Age	---	---	-0.12*	.
	Gender	0.12*	.	---	---

Significance levels: <0.001 ‘***’, < 0.01 ‘**’, < 0.05 ‘*’, >0.05 ‘.’, not applicable ‘---’,
HK: Health knowledge

In Bishil/Sarag, the strongest and most significant (p<0.001) global spatial clustering was detected among males. These clusters were positively associated with housing quality, sanitation, and environmental health knowledge; however, they were negatively associated with “natural environment”, a regression factor including the amount of vegetation and water around households, as well as the distances to streets (cf. Table V-1). To some extent, we also found that spatial clustering among females in Bishil/Sarag was positively associated with flood non-affectedness, housing quality, and education, as well as being negatively associated with age. Within Bishil/Sarag, we also found spatial clustering to be additionally correlated with income generation among young adults. In Abdullapur East and Kunipara, we found spatial clustering of WHO-5 scores only when using a large neighbourhood of the 10 nearest neighbours of respondents (mean distances ranging from 35 to 57 meters). In addition, we found that within slums and within population groups, the strength and significance of spatial autocorrelation differed with the type of neighbourhood relation. For example, spatial autocorrelation among males in Bishil/Sarag decreased when more neighbours or longer distances were considered in the analysis; the same was true among young adults in Beguntila (Table VI-1). Therefore, the global univariate Moran’s *I* of the response variable (WHO-5 scores) reflect the spatial variation at the scale of the settlements. Focussing on health-determining factors (HDF) with the global bivariate, Moran’s *I* revealed a similar spatial pattern at the scale of the settlements (cf. Figure VI-4).



	3nn	5nn	10nn
WHO-5 scores	0,19	0,17	0,01
WHO-5 ~ natural environment	-0,21	-0,21	-0,19
WHO-5 ~ housing quality	0,30	0,26	0,23
WHO-5 ~ sanitation	0,18	0,13	0,12
WHO-5 ~ env. health knowledge	0,13	0,10	0,10

Figure VI-4: Moran's *I* values for males in the slum settlement Bishil/Sarag. Significant global univariate and bivariate Moran's *I* values for mental health (WHO-5 scores) and spatially correlated health determining factors are shown for different nearest neighbours. Note that the Moran values decrease as the number of neighbours increases.

Local cluster maps derived using Anselin's Local Moran's *I* statistic (local univariate Moran's *I*) (Anselin 1995) were used to calculate the type and location of the clusters detected. Because clustering was strongest and most significant in Bishil/Sarag, we concentrate on this slum in the following analysis. We found that for this settlement, well-being among males was spatially structured in the west and east, with poor well-being localised predominantly in the western area and good well-being in the eastern part of the settlement (cf. Figure VI-5). Furthermore, the local bivariate Moran's *I* statistic revealed that low WHO-5 scores were associated with poor housing quality in the western part of Bishil/Sarag, whereas high WHO-5 scores and better housing quality were clustered in the east. "Natural environment" was found to be negatively correlated with well-being: in the western area, a higher amount of "natural environment" could be found, together with poor well-being clusters (cf. Appendix, Figure B-1). In contrast to the spatial clustering of males, both patterns of good and poor well-being appeared among females in the western part of Bishil/Sarag. For more detailed maps, please refer to the Appendix B.

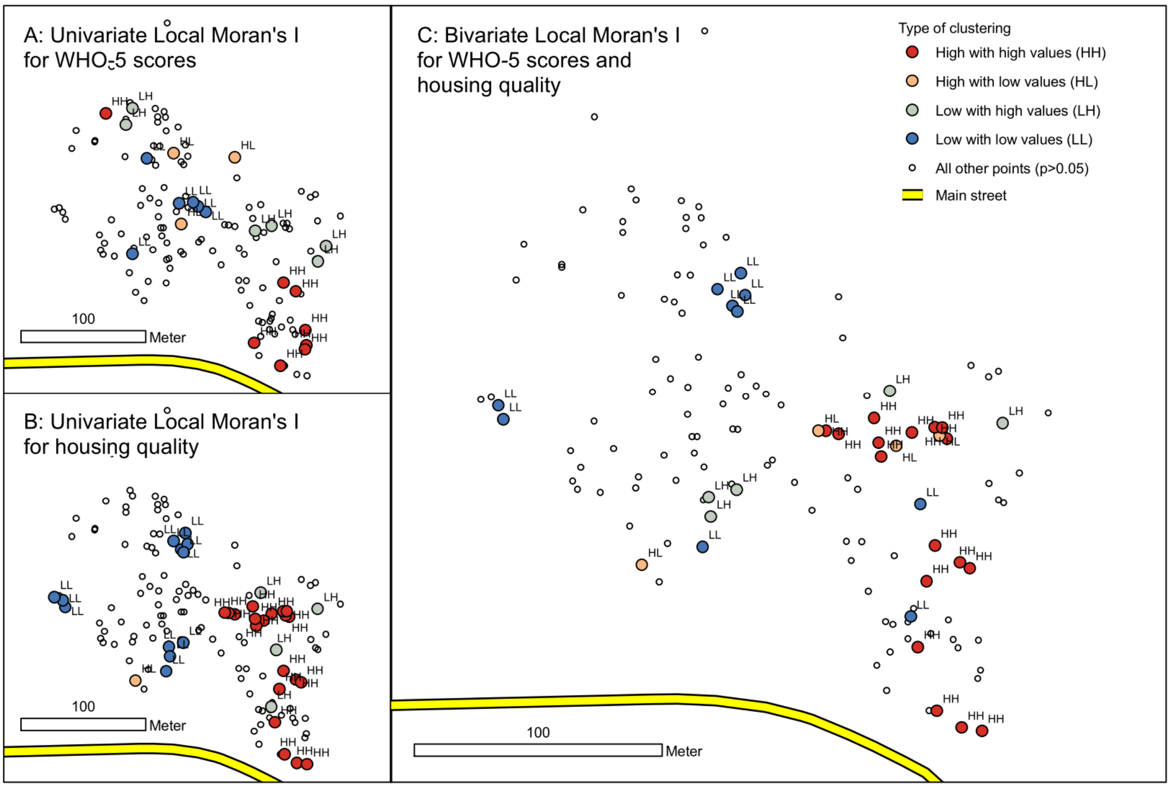


Figure VI-5: Mental health (WHO-5 scores) and housing quality of males in the slum settlement Bishil/Sarag. Each dot on the map indicates a slum household (GPS point). The maps indicate significant ($p<0.05$) spatial clusters of high (HH) or low (LL) WHO-5 scores (A), housing quality (B), or similar values of both WHO-5 scores and housing quality (C), respectively. High values surrounded by low values (HL) and vice versa (LH) indicate outliers. The three nearest neighbours of a household were used in the statistics.

4 Discussion

We investigated the hypotheses that mental health shows a significant spatial pattern (e.g., spatial clustering) for different population groups, and that the spatial patterns relate to spatially-correlated health-determining factors (HDF), for example, housing quality or income generation ability. Individual characteristics such as age or gender are associated with health and give rise to a unique spatial structure among the health status of different population groups. Although gender was (surprisingly) not associated with mental health in our non-spatial ANOVA, we investigated spatial structures separately and found different spatial patterns for both groups, which supports our first hypothesis. For the neighbourhood defined by the three nearest (sampled) neighbours, we provided evidence that clustered households/respondents contrast strongly with other households/respondents in different clusters with regard to their well-being. Hence, it can be stated that first, there are substantial health inequalities in slums. The investigated patterns showed a spatial dependence of well-being at one location on the well-being of a neighbouring location (i.e. they were spatially auto-correlated). A possible explanation is that good mental health in a neighbourhood may support salutary effects in the social fabric, and vice versa (Gee and Payne-Sturges 2004). With regard on our second hypothesis, we were able to show that the association between individual characteristics such as age or gender and mental health status in slums is often indirect and can be heavily influenced by other factors such as neighbourhood socio-physical characteristics. These factors are believed to shape the distinct vulnerabilities and the resilience of residents towards ill health.

Many of those HDF, which in our first study were found to be associated with well-being (cf. Chapter V), remained significant in the spatial bivariate analysis taking into consideration each slum separately. The example of Bishil/Sarag showed that the spatial distribution of e.g. higher values of the “natural environment”, flood affectedness and poor housing quality as well as poor sanitation was correlated with the spatial distribution of poor well-being and vice versa. Thus, we did not only provide evidence that the well-being of slum residents is associated with certain HDF in the same households, but that well-being is also associated with HDF prevalent in the immediate neighbourhood of a respondent’s home. In other words, neighbourhood clusters, which constitute significantly better or poorer well-being in comparison to the other neighbourhoods of a slum, also comprise similar HDF that are related to their respective health status. Hence, the local neighbourhood may be defined by the (spatially) prevailing HDF factor in that area.

In our study, the strength of spatial clustering decreased with increasing neighbourhood size – regardless if the neighbourhood was defined based on nearest neighbours or with a distance based approach. We demonstrated this by the mental well-being among males in Bishil/Sarag, but the pattern could also be revealed by the HDF for this population group. This spatial pattern could also be verified among other population groups within the same slum and in Beguntila. Overall, it can be stated that such spatial patterns point to small-scale effects within the slums, indicating that autocorrelation effects and the spatial effects of HDF take place at short distances. Moreover, our results provide evidence that model outcomes are sensitive to different definitions of neighbourhood relation. Considering that spatial patterns of health status uncover health disparities and provide the basis for further analysis, our study helps to determine the feasibility of using a particular statistical method to avoid violating the assumption of data independence that underlies most non-spatial statistical approaches (Waller and Gotway 2004; Schabenberger and Gotway 2005; Bivand et al. 2008). For subsequent analyses on health and the environment in the spatially autocorrelated settlements, any statistical model used has to be extended to account for the particular spatial dependence in the data. Identifying an appropriate neighbourhood relationship for a variety of spatial analysis methods is thereby a crucial endeavour.

5 Conclusions

Adding to the existing literature on public health in slums, we were able to contribute empirical evidence for the local variation of well-being in selected slums of Dhaka. We conclude that the WHO-5 Well-being Index is an easy-to-use and quickly assessed measure for mental health in slums. The WHO-5 scores were positively correlated with other health outcomes such as “self-rated health” and negatively with “having had a disease”.

Knowledge of the spatial distribution and structure of one's health status may help us to understand a community's social fabric and its related mental health-determining factors, but most importantly, it allows for a more efficient and effective spatial allocation of scarce resources to target the alleviation of poverty and the improvement of living standards. Because our methodology provides evidence for spatial dependencies in epidemiological data, it might lead to more sophisticated spatial epidemiological models that create a deeper understanding of functional relationships between mental health and the environment. In addition to examining health outcomes, our methodology can also be adapted to investigate regression residuals and thus help avoid the violation of data independence that underlies many statistical approaches. Spatial epidemiological models could thus lead to improved rationales for public health interventions and might strengthen policy significance. This type of approach is of vital relevance in developing specific strategies for improving the lives of slum dwellers in Dhaka and in comparable settings worldwide.

We argue for a more widespread use of spatial epidemiological approaches in similar public health studies because we assume that our conclusions are relevant for other studies in the slums of developing countries.

Chapter VII:
Putting mental health into spatial context – a neighbourhood study in the slums of Dhaka

1 Abstract

Background

Geo-referenced public health information for urban slums in developing countries is rare, as are neighbourhood studies on mental well-being of slum dwellers. The goal of this study was to investigate the conditions of local spatial neighbourhoods and their associations with mental health among slum residents in Dhaka.

Methods

Baseline data from a 2009 cohort study in nine slums in Dhaka (n=1,938) were analysed. The WHO-5 Well-being Index was used as a measure of self-rated mental health. We used a spatial epidemiological approach that compares a generalised linear (GLM) with a generalised linear mixed model (GLMM). In an exposure mapping approach using indices of local spatial autocorrelation (Local Moran's *I*), mental health-determining factors (HDF) were identified where they cluster in the local neighbourhood. Applying a GLM helped to identify significant mental health related neighbourhood conditions (spatial HDF-clusters). Thereby, the HDF-clusters were used as explaining variables, adjusted by individual level characteristics, such as age, gender, or education and other socio-physical environmental variables. In order to test for neighbourhood associations with mental health, a GLMM was applied. We tested for a two-level hierarchical structure (individual as the 1st and slum as the 2nd level) and also for a three-level hierarchical structure (individual as the 1st, spatial HDF-cluster as the 2nd, and slum as the 3rd level).

Results

In addition to good personal income generation, job satisfaction, housing quality, housing sufficiency, housing durability, sanitation, and flood non-affectedness, living in a neighbourhood with prevalent insufficient housing was positively associated with mental health. Besides high personal crowded housing conditions and features of the natural environment, mental health was negatively associated with living in a neighbourhood with good environmental health knowledge and also with prevailing good basic services. Neighbourhoods or slums alone could not explain much of the variance in the data. However, the GLMM did outperform the GLM with respect to the remaining spatial autocorrelation.

Conclusions

Mental health in urban slums is affected by a wide variety of factors and cannot be fully explained by a statistical model. When studying slums, small scale variations need to be considered. We showed that spatial indices can be used to define the local neighbourhood. Socio-physical features from the local neighbourhood affect mental health differently from personal and household level characteristics. Our methodology provides an example for future urban health studies and may improve the understanding of the complex relationship of urban mental health and the socio-physical environment.

Public health in slums is well known to be threatened by the residents' exposures to environmental pollution, by poor basic services of water and sanitation, or by inadequate access to social and health care services (Riley et al. 2007). However, few studies have investigated distinct social and physical neighbourhood characteristics in slums. Moreover, quantitative analyses of mental health status in relation to neighbourhood contexts are still rare.

In cities of higher income countries, it has been shown that neighbourhood contexts have substantial effects on the health status of local residents. For example, neighbourhood socio-economic status (SES) (a contextual factor) is associated with the (mental) health of urban residents independently from personal SES (Fournoy and Yen 2004; Galea et al. 2007; Ompad et al. 2007). Through our studies (Chapters V and VI), we were able to show that mental health was diversely associated with various socio-physical environmental factors and that mental health was unequally distributed in the slums of Dhaka both spatially and among population groups. In this chapter, we assumed that the spatial inequalities in mental health evolved from different socio-physical features i.e., from the neighbourhood context of slum residents. Therefore, we aimed to investigate the associations of neighbourhood context with mental health in slums. Our goals were (i) to characterise the contextual factors of neighbourhoods in slums and (ii) to identify associations of these factors with the mental health of local slum residents. We investigated the hypotheses that neighbourhood contextual factors exist in slums and that these factors affect mental health differently than individual-level exposures.

Similar to our previous work (Chapter VI), a spatial epidemiological approach to mental health was applied. This time, however, we first used exposure mapping to identify contextual factors in the neighbourhood. With exposure mapping, (i) the spatial extent of neighbourhood influences can be defined, and (ii) spatial clusters of "neighbourhood" types can be identified, such as clusters of poor housing or of good health knowledge. Spatial clusters can be diverse, and an individual or household may reside in distinct "neighbourhoods" (i.e., spatial clusters) that may form, for example, a spatial cluster of poor housing and a cluster of good health knowledge at the same time. Furthermore, the spatial clusters may not completely overlap. For example, one of these might be larger than the other.

Second, we used a generalised linear model (GLM) as well as a generalised linear mixed model (GLMM) to identify associations between mental health and neighbourhood contextual factors that were previously found by exposure mapping.

Using a bivariate model in Chapter VI, analyses were separately performed for each slum and population group. By applying a multivariable model (GLM or GLMM) in this study, we were able to analyse our data across all slums while accounting for individual and neighbourhood level factors. Because one of our goals was to identify associations of the contextual factors of neighbourhoods with the mental health of local slum residents, we were also investigating how much variance could be explained by neighbourhood or slum alone.

When individuals/households belong to a spatial cluster (neighbourhood), they typically share the same features of the socio-physical environment as do their neighbours (cf. Anselin 1995). Hence, the outcome (mental health) is not independently distributed. In other words, the outcome may be nested within neighbourhoods. In contrast, a traditional linear regression (e.g., a GLM) assumes the independence of the observations that are conditional on the explanatory variables and uncorrelated residual errors, although these assumptions may be violated for nested data structures (Twisk 2006). One promising approach for the analysis of nested data is multilevel modelling (e.g., with a GLMM) that allows one to simultaneously examine the effects of group-level and individual-level variables on individual-level outcomes while accounting for the non-independence of observations within groups.

2 Methods

2.1 Exposure mapping

We used the baseline data of the cohort study described in Chapter IV. The WHO-5 was used as a measure of mental health. Although conceptualised at distinct levels, all variables were measured for each observation, allowing for individual-level analysis (cf. Table V-1). However, this did not enable the analysis of a neighbourhood's association with one's well-being. Thus, we used exposure mapping to identify the likely spatial patterning of HDF. The identified spatial patterns were subsequently tested for a likely association with mental health in multivariable regression models (cf. Figure VII-1).

Spatial autocorrelation analysis

Our previous work has shown that mental health was best described by a multivariable regression model containing 16 HDF (cf. Chapter V). In this study, we applied a spatial autocorrelation (SAC) analysis on the residuals from that multivariable model, which we term "raw GLM" from now on (cf. Table V-2 for the variables used in this model). Global Moran's *I* values on the residuals were calculated for six different neighbourhood relationships (i.e., we used k values of the 3, 5 and 10 nearest neighbours and all neighbours of a sample household in distances of 30, 60, and 90m). We selected the neighbourhood relationship with the largest global Moran's *I* values for the subsequent computation of the HDF-cluster variables. We used 9,999 randomised draws from the data to identify significant values. Please refer to the methods section of Chapter VI for details on the neighbourhood relationships, global and local (univariate) Moran's *I* statistics, and the permutation test. Global Moran's *I* statistics were computed using the statistical package spdep (Bivand et al. 2009) available in R (R Development Core Team 2010).

Neighbourhood-dummy variables

For each of the HDF variables, local Anselin Moran's *I* values were computed. Using these Moran's *I* values, cluster types were calculated (cf. Chapter VI). Depending on the type of clustering, dummy variables were created, coded 1 for high values of a household's socio-physical features (e.g., good housing quality) that are next to other households comprising similar high values of the same socio-physical features (HH) or vice-versa (LL) or coded 0 for all spatial outliers and for insignificant observations. Hence, 22 HDF variables resulted in 44 neighbourhood-dummy variables, with each representing either a HH or a LL HDF cluster. The neighbourhood-dummy variables were subsequently used as explanatory variables in multivariable regression models (GLM and GLMM), which represented the local neighbourhood's contextual or compositional factors. Local spatial analysis was applied in GeoDa (Anselin 2004).

2.2 Spatial epidemiological modelling (GLM)

While in Chapter VI the focus was on each separate slum, we consider all slum residents in this Chapter in order to account for a larger sample size. We analysed the residents' neighbourhood contexts (with neighbourhood-dummy variables) and controlled for the hypothesised confounding factors (16 HDF variables) via multivariable modelling. Each of the 44 neighbourhood-dummy variables was included in a separate generalised linear regression model (i.e., the raw model from Chapter V, cf. Table V-2), which included the other 16 HDF variables, assuming a negative binomial distribution of the target variable mental health (cf. Chapter V). A total of 44 multivariable regression models were therefore applied (i.e., 22 HDF variables resulted in 44 neighbourhood-dummy variables, each representing either a HH or a LL HDF cluster). All significant neighbourhood-dummy variables were then included in the “full GLM” in order to facilitate comparisons with the GLMM.

We calculated correlation coefficients for the explanatory variables in order to test for multicollinearity. We removed collinear (above a threshold of 0.5) HDF variables from the model. A regression analysis was conducted with the statistical package MASS and the function “glm.nb” (Venables and Ripley 2002) available in R (R Development Core Team 2010). An SAC analysis was applied on the model residuals with the abovementioned methods.

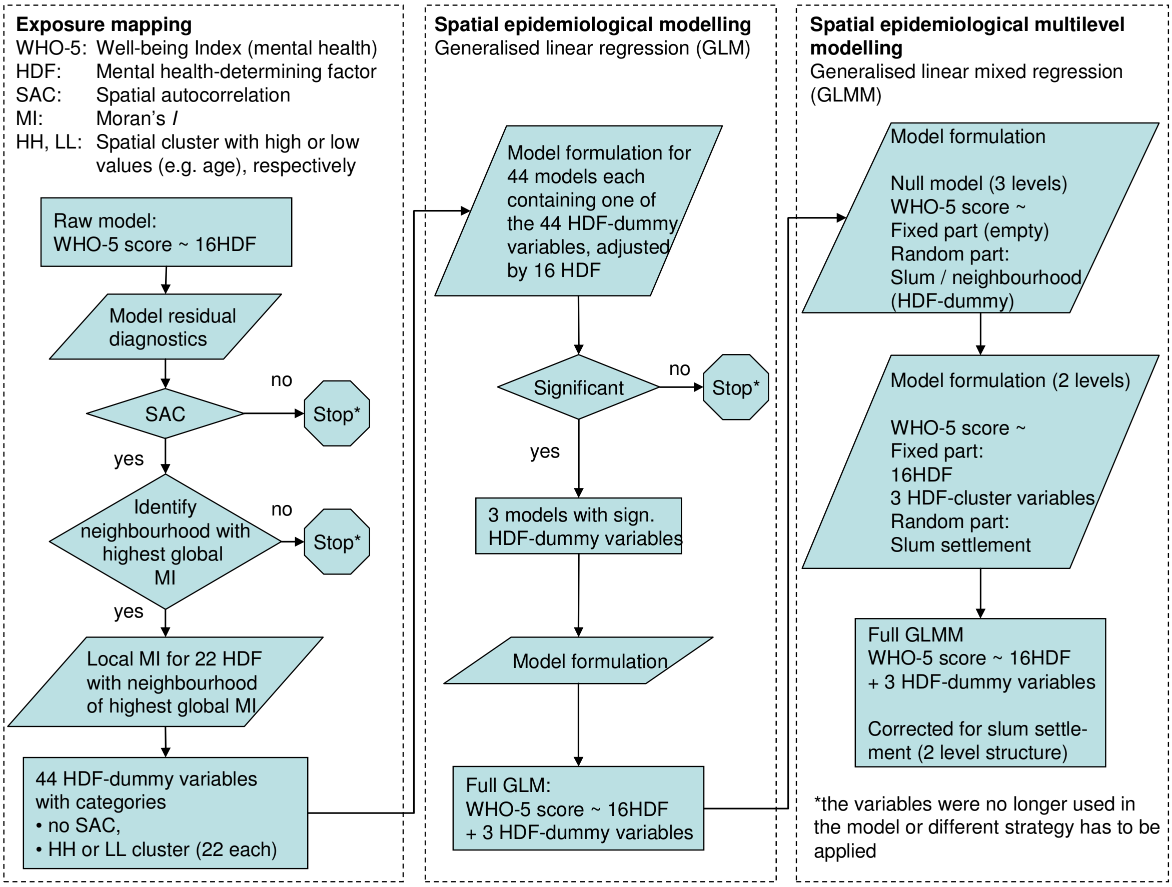


Figure VII-1: Methodology used for this study. Parallelograms stand for statistical processes, rhombuses for selection criteria and rectangles for outcomes.

2.3 Spatial epidemiological multilevel modelling (GLMM)

A mixed model consists of a structural (fixed) effect and a random effect. Random effects describe the effect of factors that are assumed to act at random (i.e., the effect cannot be attributed to a specific factor level). Group structures, such as block numbers, zip codes or, in our case, slum names or neighbourhood types, are typical for effects of factors that act at random. Therefore, it does not make sense to estimate the random effect itself; instead, the parameters of the random distribution are estimated (Zuur et al. 2009).

So, one of the advantages of multilevel analysis (e.g., with mixed models) in comparison to a linear regression model with dummy variables (e.g., to test for the effect for each neighbourhood or slum) is that there is no need to calculate the intercepts for all dummy variables. Instead, only the variance of the intercepts is estimated (i.e., the random intercept) (Twisk 2006). As residents who live in the same neighbourhood are supposed to be more similar to each other than to residents of a different neighbourhood because they share the same socio-physical environments, it is likely that observations within neighbourhoods are correlated, which requires a statistical correction. Because of this correlation, it can be said that there is a two-level hierarchical structure in the data (Twisk 2006), with potential intra-group correlations between individuals/households living in the same neighbourhood (1^{st} level) and between the neighbourhoods (2^{nd} level). It could also be assumed that there is a three-level structure in the data, with the individuals/households as the 1^{st} level, local neighbourhoods as the 2^{nd} level, and the slum settlements as the 3^{rd} level. With the multilevel model, we wanted to (i) investigate how much variance could be explained by the neighbourhood or slum alone and, while including explanatory variables for the neighbourhood and personal characteristics, (ii) account for the association of local neighbourhoods with mental health. Therefore, we strived to prevent the violation of the data independence assumption that underlies many statistical models.

For (i), we estimated the variances of the intercept for mental health using the random intercept null model (i.e., without any explanatory variable) because this enabled the identification of the proportion of variance change of each neighbourhood or slum settlement (Merlo et al. 2005; Hox 2010). The proportion of the variance in the WHO-5 scores that occurs at the 2^{nd} level (slum settlement) can be quantified with the intra-class correlation coefficient (ICC). The ICC for the 2^{nd} level is given by (Hox 2010: 33):

$$ICC = \frac{\sigma^2_{\mu_0}}{\sigma^2_{\mu_0} + \sigma^2_{\varepsilon}}, \qquad \text{(Equation VII-1)}$$

where $\sigma^2_{\mu_0}$ is the variance between slum settlements (2nd level), and σ^2_{ε} the variance between individuals/households from the same slum (1st level). For a three-level structure, with slum settlements as the 3rd level and local neighbourhoods as the 2nd level, the ICC is given by (Hox 2010: 34):

$$ICC = \frac{\sigma^2_{v_0}}{\sigma^2_{v_0} + \sigma^2_{\mu_0} + \sigma^2_{\varepsilon}}, \qquad \text{(Equation VII-2)}$$

where the variances at the 1st (individual/household), 2nd (neighbourhood) and 3rd levels (slum) are $\sigma^2_{\varepsilon}, \sigma^2_{\mu_0}, \sigma^2_{v_0}$, respectively. In either method, the ICC is a measure of correlation within the groups (e.g., neighbourhood or slum). Low values of ICC indicate low clustering within the groups (Twisk 2006).

For (ii), we used the full GLMM containing the significant explanatory variables, which were also used for the GLM. For the full model, we only used a two-level hierarchical structure (individual 1st and slum 2nd level) because the neighbourhood-dummy variables were included as explanatory variables to account for their association with mental health.

We applied a GLMM using Penalised Quasi Likelihood estimation (PQL), assuming a negative-binomial distribution of the data (cf. Chapter V). Multilevel regression analysis was applied with the statistical package MASS and the function “glmmPQL” (Venables and Ripley 2002) available in R (R Development Core Team 2010). An SAC analysis was applied on the model residuals with the abovementioned methods.

3 Results

3.1 Spatial patterns of neighbourhood exposure

Small residual SACs (global Moran's *I* values) were found, and Global Moran's *I* values were strongest with the three nearest neighbours (cf. Table VII-1). We thus used this neighbourhood relation for the local Anselin Moran's *I* statistic (Anselin 1995), which was applied to all covariates (HDF) separately (cf. Table VII-2 for the mean values of selected HDF variables for the nine slums). From Table VII-2, it becomes evident that basic services were mainly spatially clustered in Abdullapur West and East and that housing sufficiency was mostly clustered in Bishil/Sarag and Adabar. Furthermore, environmental health knowledge had the largest spatial autocorrelation in Bishil/Sarag and Kunipara. Local Moran's *I* values were used to identify the type and location of the spatial clusters (local neighbourhoods) within the settlements (cf. Figure VII-2). For example, the spatial clustering of basic services in Abdullapur West and East turned out to be large neighbourhoods in which basic services were prevalently poor (LL cluster). In Bishil/Sarag, small neighbourhoods with poor housing sufficiency were identified where poor environmental health knowledge was widespread. Furthermore, we found neighbourhoods of prevailing good housing sufficiency in Adabar and of good environmental health knowledge in Kunipara (HH cluster). But how are these living environments (neighbourhoods) associated with the mental health of local residents?

Table VII-1: Global Moran's *I* for the target variable WHO-5 score (mental health) and model residuals. We first defined 44 models (raw GLM updated by each one of the 44 HDF-cluster variables) to find significant HDF cluster variables (shown in the table). We then included all three significant variables in the model (full GLM, full GLMM). For comparison, we also provided information on the residuals from the Null GLMM (i.e., the multilevel model without any explanatory variables but with a random intercept term). Mean distances for the nearest neighbour relationships are also given. Note that there was no significant residual spatial autocorrelation with the full GLMM. For all other model residuals as well as for the outcome (WHO-5 scores), strongest spatial autocorrelation was found with the three nearest neighbours.

Neighbourhood relationship for total population across slums	**WHO-5 score**	**GLM residuals**					**GLMM residuals**	
		Raw	**Environmental health knowledge**	**Housing sufficiency**	**Basic services**	**Full**	**Null**	**Full**
Nearest neighbours								
3 nn *(10.3 meters)*	0.07***	0.06***	0.06***	0.06***	0.06***	0.06**	0.05**	0.03.
5 nn *(13.2 meters)*	0.05***	0.05***	0.05***	0.05***	0.05***	0.05***	0.03*	0.01.
10 nn *(19.2 meters)*	0.05***	0.04***	0.04***	0.04***	0.04***	0.04***	0.02*	0.003.
Fixed distance								
90m	0.05***	0.04***	0.05***	0.05***	0.05***	0.05***	0.002***	0.008.

Significance levels: <0.001 '***', < 0.01 '**', < 0.05 '*', >0.05 '.' For the 30 m and 60 m fixed distances, empty neighbourhood sets were found and the statistic were hence not applicable.

Table VII-2: Mean Local Moran's *I* values for selected HDF variables by slum.

Slum		**Basic services**		**Housing sufficiency**		**Environmental HK**	
	N	**Mean**	**StD (Se)**	**Mean**	**StD (Se)**	**Mean**	**StD (Se)**
Abdullapur West	201	2.16	1.7(0.12)	0.17	0.75(0.05)	0.03	0.21(0.01)
Abdullapur East	180	1.6	1.92(0.14)	0.04	0.37(0.03)	0.01	0.08(0.01)
Beguntila	176	1.04	0.99(0.07)	0.13	0.65(0.05)	0.17	0.72(0.05)
Bishil/Sarag	253	0.01	0.05(0)	0.17	0.67(0.04)	0.99	2(0.13)
Adabar	176	0.17	0.43(0.3)	0.19	0.53(0.04)	0.2	0.85(0.06)
Kunipara	247	0.05	0.23(0.01)	0.04	0.39(0.02)	0.32	0.52(0.03)
Buhiapara	217	0	0(0)	0.01	0.12(0.01)	0	0(0)
Kamrangir Char	211	0.03	0.16(0.01)	0.14	0.61(0.04)	0.02	0.12(0.01)
West Jurain	244	0.01	0.05(0)	0.14	0.67(0.04)	-0.01	0.12(0.01)

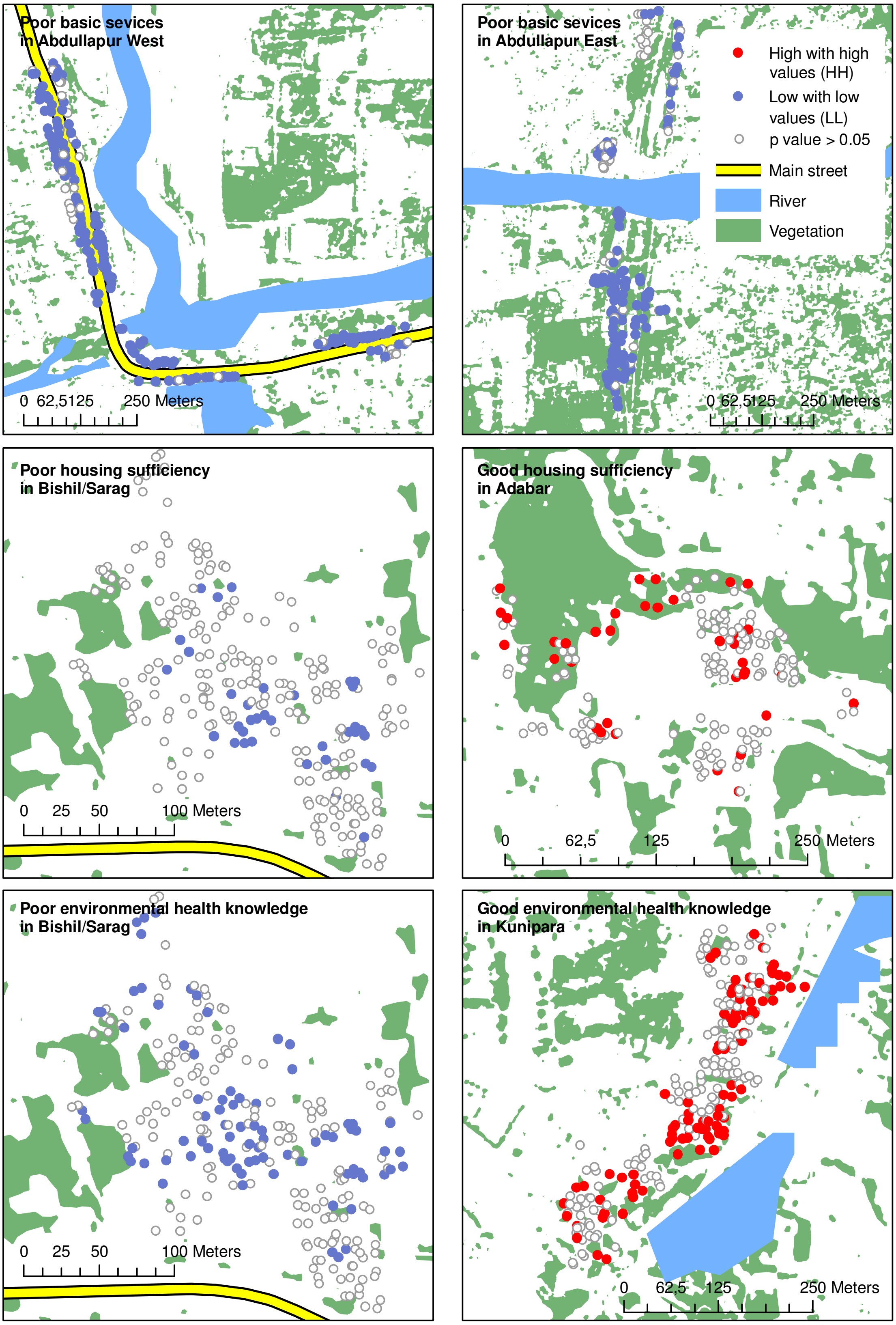


Figure VII-2: Local neighbourhoods (spatial clusters) that comprise the low (LL) or high values (HH) of the mental health-determining factors (HDF) are displayed for selected slum settlements in Dhaka.

3.2 Mental health in the context of local neighbourhoods

Respondents sharing the same neighbourhood (i.e., a cluster of spatially correlated socio-physical environmental exposures) experience different health outcomes in comparison to other slum residents (cf. Table VII-3). For example, mental health was negatively associated in a spatial cluster of neighbours with good environmental health knowledge (HH cluster). A neighbourhood with prevailing insufficient housing (LL cluster) was positively associated with the mental health of the residents within this cluster. Furthermore, a neighbourhood with a pervasive higher availability of basic services (i.e., water supply, electricity, or access to public park areas) (cf. Table V-1) (HH cluster) was negatively associated with the residents' mental health. The models were capable to explain 20% of the variance in the data.

However, when the three significant neighbourhood-dummy variables in the GLM were concurrently included and controlled by the other 16 HDF (full GLM), only one neighbourhood-dummy variable remained significant. As such, insufficient housing remained positively associated with mental health (cf. Table VII-3). Allowing for random intercepts between the slums (full GLMM) supported the positive association of surrounding insufficient housing with mental health. Additionally, neighbourhoods with good environmental health knowledge again had a significant negative association with mental health.

The variation between the slums was small. The highest obtained ICC value for the Null model was 0.008, meaning that 0.8% of the variance in mental health was explained by the slum settlements alone. Hence, the location of a household in a particular slum did not shape mental health. Small ICC values were also identified for the between-neighbourhood variances within the slums (cf. Table VII-4). For example, neighbourhoods defined by good basic services could explain 0.7% (ICC=0.007) of the variance. The within-neighbourhood variance was greater than the between-neighbourhood and the between-slum variances. However, the multilevel model reduced the spatial autocorrelation of the model residuals despite the low clustering within the slums and the neighbourhoods (cf. Table VII-1).

Table VII-3: Determinants of mental health. Adjusted by age, sex, disease, migrant, community membership, environmental knowledge and personal health knowledge. The raw GLM is the multivariable regression model found in Chapter V (cf. Table V-2) and includes only one of the neighbourhood-dummy variables at a time. The full GLM and full GLMM include all neighbourhood-dummy variables that were found to be significant in the raw GLM. Note that for the full GLMM, we applied a 2-level structure to account for the impact of the neighbourhood-dummy variables.

	Raw GLM			**Full GLM**	**Full GLMM**
Neighbourhood-dummy variable	Environmental health knowledge	Housing sufficiency	Basic services		
Null model intercept, StD (SE)					2.16 0.1(1.1)
Model intercept (95% CI)	2.42 (2.31/2.53)	2.39 (2.29/2.5)	2.42 (2.31/2.53)	2.42 (2.31/2.53)	2.43
WHO-5 ~ HDF	**Coef. (95% CI)**				
Natural environment	-0.06*** (-0.08/-0.03)	-0.05*** (-0.08/-0.03)	-0.05*** (-0.08/-0.02)	-0.05*** (-0.08/-0.03)	-0.06**
Flood non-affectedness	0.07*** (0.04/0.09)	0.06*** (0.04/0.08)	0.07*** (0.05/0.1)	0.07*** (0.05 / 0.1)	0.07***
Housing quality	0.03** (0.01/0.06)	0.04** (0.01/0.06)	0.02.	0.03* (0.002 / 0.05)	0.02.
Sanitation	0.08*** (0.05/0.01)	0.08*** (0.05/0.01)	0.08*** (0.06/0.11)	0.08*** (0.05/0.1)	0.09***
Housing sufficiency	0.07*** (0.04/0.09)	0.08*** (0.05/0.1)	0.07*** (0.04/0.09)	0.07*** (0.05/0.1)	0.07***
Housing durability	0.07*** (0.05/0.09)	0.07*** (0.05/0.09)	0.07*** (0.04/0.09)	0.07*** (0.04/0.09)	0.07***
Population density	-0.05*** (-0.07/0.02)	-0.05*** (-0.08/0.02)	-0.05*** (-0.07/-0.02)	-0.05*** (-0.08/-0.02)	-0.05***
Job satisfaction	0.08*** (0.06/0.11)	0.09*** (0.06/0.11)	0.08*** (0.06/0.11)	0.08*** (0.06/0.11)	0.09***
Income generation	0.08*** (0.06/0.11)	0.08*** 0.06/0.11	0.08*** (0.06/0.11)	0.08*** (0.06/0.11)	0.08***
HDF-dummy					
Environmental health knowledge					
no SAC	Reference	---	---		
HH	-0.1* (-0.19/-0.01)	---	---	-0.09.	-0.11*
Housing sufficiency					
no SAC	---	Reference	---		
LL	---	0.12* (0.02/0.23)	---	0.13* (0.02 / 0.23)	0.14*
Basic services					
no SAC	---	---	Reference		
HH	---	---	-0.11* (-0.2/-0.02)	-0.9.	-0.07.

Table VII-4: ICC values for the Null model (GLMM) at three levels. The 1st level was individuals/household, the 2nd was the within-slum neighbourhood (spatial cluster of environmental health knowledge, housing sufficiency or basic services), and the 3rd level was the slum settlement.

	Environmental HK HH	**Housing sufficiency LL**	**Basic services HH**
Between slum variance	0.01	0.01	<0.001
Between neighbourhood variance	<0.001	<0.001	0.01
Within neighbourhood variance	1.2	1.2	1.2
ICC between slum	0.008	0.008	<0.001
ICC between neighbourhood (within slum)	<0.001	<0.001	0.007

4 Discussion

Using a multivariable analysis across all slums, we investigated the hypotheses that different socio-physical neighbourhoods exist and that these neighbourhood contexts show different associations with mental health compared to individual-level exposures.

Our analysis identified a negative association of prevailing good health knowledge in the neighbourhood context with one's mental health. We assumed that all residents within that neighbourhood were aware of possible health threats arising from environmental pollution. This might have led to increased stress levels, as the slum residents had to knowingly deal with deprived environments on a daily basis.

A neighbourhood of general insufficient housing (i.e., poor light in the room/house that was not regarded as sufficient for the family and that was also used for other purposes besides being a living space) was also found to be a significant contextual factor. Pervasive insufficiency of the houses in an area (including one's one house) was positively associated with the mental health of the residents. We were unable to specifically explain this phenomenon but assumed that other factors may play a role, which were likely to be correlated with poor housing. For example, when houses are not sufficient for families and their neighbours, people may be engaged in activities to improve their neighbourhood, which may produce solidarity and a common identity that ultimately could result in better mental health status among the local residents.

Another significant contextual factor was the availability of basic services in the local neighbourhood. Examples for basic services are water supply, electricity, and access to public park areas (cf. Table V-1). Neighbourhoods with prevailing higher accessibility to basic services were found to be negatively associated with mental health. We supposed that these areas were highly contested or comprised underlying difficulties for the residents, which were associated with better basic services. For example, in many informal settlements of Dhaka, it is quite common to negotiate prices for tapped water with unofficially appointed field inspectors of the local water supply authority (DWASA) and to install illegal pumps or additional unofficial parallel water connections to secure a water supply. Those who have a strictly official attitude and do not participate in these illegal practices may be forced to pay higher prices for water. Hence, an official water connection with installed meters is not only more expensive but also viewed as foolish from the perspective of a local community (Hossain 2011).

Slum settlements in Dhaka cannot be regarded as classic neighbourhoods; rather, they have to be considered as small "villages" within a megacity with different socio-physical neighbourhoods contained within it. Nevertheless, the small variances between the settlements (0.8%) and neighbourhoods (0.7% for good basic services) provide evidence that there was a negligible correlation between the observations within a slum or neighbourhood. Thus, slum settlements or neighbourhoods alone could not help to explain the differences in mental health outcomes. Mental health was, on the other hand, shaped by the diverse local socio-physical neighbourhoods in combination with individual assessed exposures and characteristics.

In Dhaka's slums, small-scale effects on the associations between HDF and mental health were identified. Small-scale effects such as the spatially autocorrelated residuals from the multivariable regression analysis that were prevalent at 10.3m within the slums are likely due to spatial dependencies of the target variable (mental health) or to spatially autocorrelated explanatory variables (HDF). In any case, the multilevel model with the nine slum settlements as the 2^{nd} level eliminated the residual spatial autocorrelation. Despite the small between-group correlations, the multilevel approach that accounted for the individual, neighbourhood, and slum level exposures in Dhaka's slums improved the outcomes of our study.

5 Conclusions

Where an individual lives determines his or her mental health, independent from the various individual and household factors, even within the same slum. We showed that the contextual features within the slums were unequally distributed. We also analysed the importance of such neighbourhood conditions and their associations with mental health. We found that good health knowledge and basic services were negatively associated with mental health when they were prevalent in the neighbourhood. However, insufficient housing in the neighbourhood was positively associated with mental health.

Furthermore, we conducted a multilevel analysis that accounted for the spatial dependencies within the slums but was not sufficient to define the neighbourhood level. The multilevel analysis returned surprisingly low between-slum and between-neighbourhood variations, which suggested a weak influence of the location of an individual in a particular slum or neighbourhood on its overall mental health. Contrary to our a priori expectations, mental health was largely shaped by individual and household-level characteristics.

When studying slums, small-scale spatial variations need to be considered. Our methodology provides an example for future urban health studies at both high spatial resolutions and at the individual level. Such investigations may improve the understanding of the complex relationship of urban mental health and the socio-physical environment. It can also lead to conclusions that enrich spatial regression analyses with a place-based understanding. As such, inferences can be drawn that may help to support health policy implementations and their spatial targets.

Chapter VIII: Synthesis & outlook

1 Summary and main findings

Mental health problems were common but not equally distributed among the urban poor. Several mental health determining factors (HDF) from the socio-physical environments were identified. Although there were some health-threatening factors, most factors were supportive of good mental health in the slums. Mental health was spatially clustered, pointing to severe health disparities within the slums. Furthermore, it could be shown that HDF were spatially clustered within the slums and that these clusters could be defined as specific neighbourhoods of prevailing HDF. Living in such neighbourhoods was associated with mental health in a different way when compared to not living in such neighbourhoods.

Research goal 1: to assess the factors that describe the mental health of poor populations residing in Dhaka's megacity slums

In a geo-epidemiological approach, the first study focused on the assessment of socio-physical environmental factors in order to identify the exposure or assets that could have damaging or salutary effects on mental health. Geoprocessing in GIS (i.e., exposure mapping) facilitated the obtainment of information regarding the presence and amount of vegetation patches or surface water, the adjacency of rivers or streets, and the accessibility to parks that was measured at the individual level. These obtained variables were combined with the survey data. Principal Component Analysis (PCA) then identified 14 HDF that explained about 60% of the variance in the data. Together with 7 more HDF comprising the personal characteristics of the respondents, these 21 HDF were considered for further analyses. A multivariable regression model was then applied to explain the mental health of respondents by the 21 HDF and by diseases as well.

Good mental health (WHO-5 scores ≥ 13) was found in only 21% females and in 25% of males. Factors that determined the mental health of urban slum residents in Dhaka were related to the socio-physical environment and individual level characteristics. Selected features of the natural environment, population density, personal health knowledge, age, and diseases were found to be negatively associated with the mental health of the respondents. Flood non-affectedness, the quality, sufficiency, and durability of housing, sanitation, job satisfaction, income generation, environmental health knowledge, and male gender were found to be positively associated with mental health. However, basic services, household wealth, smoking behaviour, the use of bed nets, marital status, and education were not significantly associated with mental health and were removed from the model. Given that mental health conditions could elevate the risk for group I (communicable diseases), group II (non-communicable diseases), and group III diseases (injuries), these findings may provide crucial information for developing better health care and disease prevention programmes in the slums of Dhaka and in other comparable settings.

Research goal 2: to investigate the spatial variability of mental health status for different population groups in slums

Individual level geo-referenced data allows for the spatial quantification of disease distribution as is usually done in disease mapping approaches. Although spatial statistics are well established to date, only a few studies have focused on the spatial distribution of mental health. With the second study, information about spatial inequalities of both good and poor mental health in slums could be obtained. Spatial patterns of mental health were detected and could be partly explained by the spatially correlated HDF. As such, the socio-physical neighbourhood was significantly associated with health status (i.e., mental health at one location was spatially dependent on the mental health and HDF prevalent in neighbouring locations). In addition to what was identified in the first study, education in one slum neighbourhood was significantly associated with mental health among females. Furthermore, the spatial patterns pointed to severe health disparities both within and between the slums.

It may be assumed that similar spatial structures are found in other studies focusing on the neighbourhood effects on health. Therefore, spatial statistics should be more widespread in epidemiological studies. This may help to develop better research approaches that are internationally comparable. For the local authorities, knowledge regarding the spatial distribution of both mental health and HDF is crucial for a better understanding of the relationship and pathways between health and the environment. Most importantly, however, such knowledge can help to advise local politicians and ultimately lead to better spatially-allocated health intervention measures.

Research goal 3: to identify whether the local neighbourhood affects mental health in slums

Urban health research is often linked to the question of roles played by local neighbourhoods in shaping urban health. An acknowledgement of spatial neighbourhoods could further the knowledge upon the aetiologies of both good and poor mental health.

However, only a few studies have investigated local neighbourhood associations with mental health in slums.

The third study applied exposure mapping to identify distinct neighbourhoods in slums and multivariable regression analyses to test for likely associations of these neighbourhoods with the mental health of slum residents, while adjusting for the other 22 HDF including diseases. It was shown that the neighbourhood in which one lives can affect one's health differently from one's own socio-physical environment. In addition to the findings of the first two studies, the third study identified living in a neighbourhood with prevalent insufficient housing as positively associated with mental health. Furthermore, mental health was negatively associated with living in a neighbourhood comprising good health knowledge and prevailing good basic services. According to the three nearest neighbours with a mean diameter of 10.3m, the identified neighbourhoods were rather small.

The body of evidence is still weak for urban mental health in developing countries. The body of evidence for mental health in slum areas is also deficient. Investigating neighbourhood effects on mental health of urban slum dwellers is a vital approach to gain knowledge upon the burden of disease morbidity in slums around the world. The third study provided evidence for a developing country's megacity but could not adequately explain the associations between slum neighbourhoods and mental health. Studies on the relationship between urban neighbourhoods and mental health (in developed countries) have almost consistently reported that deprived neighbourhoods (e.g., with low socio-economic status (SES) or higher crime rates) adversely affect individual mental health independent from individual SES (cf. Silver et al. 2002). However, the reason why the third study showed that "good neighbourhoods" (i.e., spatial clusters of good health knowledge or good basic services) negatively affected the mental health of the slum residents (and vice versa for insufficient housing) cannot be explained. Longitudinal studies on neighbourhood effects may deliver more in-depth information regarding these relationships. Additionally, social theory and qualitative social research may provide approaches that are urgently needed to find the reasons behind these relationships.

2 Advantages and limitations

Urban health is determined by a wide variety of factors. As such, research on mental health and the urban environment cannot capture all of the facets of the daily life of urban residents. The spatial epidemiological approach carried out by this dissertation was encompassed by several limitations but also enabled certain advantages for the field of urban health. This section briefly discusses these elements.

One limitation was the mental health measure. Although the WHO-5 is a reliable measure for depression screening (WHO 2010), it has never before been tested in a slum of a developing country. Furthermore, as a screening instrument, the WHO-5 does not provide evidence for depression or mental health disorders. More effort should be invested by specialists in this research domain in order to provide reliability studies from a psychological point of view. However, from this thesis, one can conclude that the WHO-5 is a fast and concise measure for assessing self-rated mental health and well-being in slums, as it only contains five questions. As such, it facilitates large study designs. Second, the natural environmental variables that were drawn from the satellite analyses were from a different year than were the outcome variables. However, a satellite image from the same season was taken in order to obtain similar phenological and hydrological situations. Third, the nine slums selected for the analysis may not fully represent all ~4,900 rather small slum clusters in Dhaka. Fourth, obtaining a representative spatial sample in Dhaka's slums was challenging because of the high population density and poor accessibility of the slum households. Hence, it was almost impossible to achieve a geographically well-distributed set of samples representing all residents living within the slums. However, the sampled data were assumed to be sufficient to analyse the spatial distribution of mental health in the slums of Dhaka. Fifth, at the time of the writing of this thesis, the follow-up data from the longitudinal study were not fully processed, and hence only the baseline data of the survey could be considered in a cross-sectional style. Therefore, the studies might hide effects that might have been discovered by longitudinal studies. Sixth, although more than 1900 persons were interviewed, only ~1600 provided valid samples for the multivariable statistics. This was due to the removal of cases that had missing data. When studying the spatial distribution within the slums, the sample sizes also decreased. However, applying multivariable regression models (GLM) helped to make use of the total sample across all slums and further supported most of the site-specific findings (i.e., for each slum separately). Furthermore, the approach suggested a linear relationship between well-being and the covariates, which might not mirror the true relationship between the variables. Seventh, the analyses might have missed some influential HDF in the model (e.g., seasonal patterns, air pollution, social capital, food insecurity, local politics, or accessibility to health care facilities or labour markets). However the findings could be well-integrated into the framework of urban mental health (Chapter II) and the base of evidence from other studies.

The first study (Chapter V) applied a geo-epidemiological approach. Since the location of each household that participated in the survey was geo-referenced, these data could easily be combined with other spatial data. Geoprocessing was used to spatially enrich the survey data using information on land cover gained from satellite images and digital cartographic maps. In this way, it was possible to describe mental health as a function of one's own social and physical environment as measured at the individual level. A conceptualisation of environmental factors according to the framework in Chapter II was challenging, as the features could sometimes be applied to both the physical and social environments. A PCA approach was applied to overcome this problem, which identified those variables that were correlated with each other. In other words, those variables that were "telling the same story" were combined with the principal components (PCs) (i.e., groups of variables in the widest sense). This approach facilitated an objective creation of the explanatory variables (e.g., household items which represented household wealth) as commonly applied with the Demographic and Health Survey (DHS) data (Rutstein and Johnson 2004). However, the challenge was to find adequate names for the identified components.

Few studies have investigated the spatial distribution of mental health. In the second study (Chapter VI), disease mapping was primarily used to generate the global and local indices of spatial dependencies among the target variable mental health. Evidence was identified regarding the existence of spatial inequalities of mental health in Dhaka's slums. These findings may raise awareness for local slum neighbourhoods and may focus attention to local problems or assets that are pertinent in these particular areas. Areas of extraordinarily low mental health status could be the first option for public health interventions, whereas neighbourhoods of predominantly high well-being could be best practices for local stakeholders. This approach also facilitated the detection of spatial dependencies in the data. A traditional linear regression assumes an independence of the observations conditional on the explanatory variables and the uncorrelated residual errors. Although these assumptions were not always met, it may be easy to account for them.

Having identified spatial clusters of mental health, spatial clusters of HDF were investigated. In the third study (Chapter VII), local neighbourhoods were defined by spatially clustered social (e.g., similar population density) or physical (e.g., similar values of housing quality) environmental factors. In other words, neighbourhoods were defined by similar contextual features, which were found to be spatially prevalent in the particular local slum areas. The usefulness of these neighbourhoods is questionable, as other neighbourhood definitions are possible. The environments that determine urban health could also be derived from the working environment or other non-spatial environments (e.g., family connections or social relationships). The main advantage of using spatial patterns based on similar environmental features was that it allowed the identification of local neighbourhoods for each slum settlement, independent of local perceptions. This helped to prevent (i) subjective and very diverse views of what is considered as the local neighbourhood by slum dwellers, (ii) arbitrarily chosen neighbourhood boundaries by formal administrative units, and (iii) neighbourhoods that were informally defined by local community leaders. This approach was thus an operable and objective measure for defining the extent and type of local neighbourhoods that allow for the quantification of likely environmental health associations. Nevertheless, it may be helpful to also acknowledge the views of the local residents and to compare our statistical neighbourhoods with the perception of what is considered as a neighbourhood by the local residents, specifically regarding the livelihood, community life, or work domain. These views may deliver additional information about the aetiologies of mental health problems prevalent in the neighbourhoods.

From a conceptual point of view, it was difficult to structure health-determining factors at the various levels of influence according to the urban mental health framework introduced in Chapter II. However, for higher levels, such as city, regional or global scales, distinct study designs would have been necessary. Also, within the levels that were used, not all of the possible health determining factors could be covered, although it was assumed that the most important ones were considered. Although it was not considered in the analyses, climate is one example among many difficulties regarding the level at which a health determining factor is thought to operate. Climate can be conceptualised at a global, regional or local level. Depending on the level under consideration, climate can have different impacts on health. Regarding urban health, a consideration of the climatic zone in which the city is located may be as important as the regional and local meso- and micro-climatic variations. These can be large within (mega-) cities, depending on the local urban environment. In brief, large sealed areas within cities contribute to the urban heat island effect, whereas large areas of vegetation can have cooling effects during seasons of higher temperatures. The global dynamics of climate change may affect local variations of the meso- and micro-climates and may increase urban heat levels. In addition, this process chain affects local levels of air pollution and their impacts on urban health. Higher levels of heat stress and air pollution are related to mental health issues. As such, climate as a health determining factor is supposed to operate at all levels in the conceptual framework of urban mental health. Due to the cross-sectional study design of this thesis, however, testing for the effect of the local meso- and micro-climate variations on mental health was not possible. The interested reader is referred to the decisive work of Burkart and colleagues who investigated bioclimate and health in both urban and rural areas of Bangladesh (Burkart and Endlicher 2009; Burkart et al. 2010, submitted; Burkart 2011; Burkart et al. 2011).

In Bangladesh, mental health conditions are not adequately served by the public sector (WHO 2006), as is the case in many other low and middle income countries worldwide. If mental health conditions are not adequately considered, health interventions are missing a substantial part of disease prevention. Furthermore, neglected urban populations, such as the developing world's slum dwellers, constitute a substantial part of the city populations. Neglecting such populations is akin to dismissing large parts of the urban society in developing countries and can hinder the adequate development of interventional strategies.

The measures that promote good mental health require a more holistic approach, which involves achieving an overall improvement in the quality of life. As such, MDGs may contribute a substantial part and may already constitute ambitious objectives to which the global community (i.e., the UN) has itself committed. Despite large successes in the fulfilment of the MDGs, however, it is of major importance to focus these goals especially on the rapidly developing megacities. While they aim to improve the overall living conditions (e.g., through environmental sustainability) (MDG 7), they can also help to reduce the burden of urban environmental pollution, which is particularly pressing in urban slum settlements. Thus, both chronic non-infectious (including mental health) and infectious diseases may then be reduced and could lead to improved treatments in those areas. Moreover, focusing on mental health issues is likely to prevent a substantial part of the population from contracting physical diseases and could also help slum residents to climb out of poverty. It is therefore necessary to put more effort in mental health research in slums with internationally comparable methods to provide more evidence at a global level. This dissertation could contribute to a better understanding of the relationship between the socio-physical environment in the slums of Dhaka and the personal characteristics of slum residents with respect to their mental health. Combining the MDGs with mental health issues might be a reasonable way to combat the double burden of poverty and disease in low-income countries. This may help stakeholders to implement better interventional strategies that are catered to those in greatest need.

3 Future research

This dissertation introduced a number of new and relevant findings that adds to the existing knowledge of mental health in urban neighbourhoods. A conceptual framework was developed, and a methodology was discussed that can quantitatively assess and analyse urban mental health in a spatially explicit way. Through an extensive survey of the slums of Dhaka, evidence was provided for inequalities at the neighbourhood context in the slums regarding their associations with the poor and good mental health status of its residents. These findings may be integrated into the existing base of evidence from other relevant studies. However, as most evidence focuses on the developed countries (Chaix et al. 2006; Diez Roux 2007; Aneshensel 2009; Harpham 2009; Diez-Roux and Mair 2010), mental health in the megacities of developing countries is still under-studied. As such, there is insufficient knowledge regarding the neighbourhood health effects in low-income countries. This section addresses possible future research direction and provides a brief discussion.

Longitudinal data provide much better empirical evidence than cross-sectional data and can thus open up a number of pathways for future analyses. One project can focus on the application of multilevel modelling to test for the effects of climate and air pollution. In Bangladesh, seasonal patterns of heat and cold effects have been identified by Burkart (2011). As it is very likely that these patterns can also affect the mental health of local slum residents, studies focusing on seasonal patterns are highly recommended. Additionally, the use of longitudinal data would help to identify additional effects of the socio-physical environment and may also help identify likely biases of the associations detected with the cross-sectional data.

Another promising approach would be a spatial scan statistic proposed by Kulldorf (1997; 2010) that could be applied in addition to the Moran's *I* statistic used in this thesis. The spatial scan statistics facilitate the detection of space-time clustering. Thus, in addition to identifying where mental health is prevalent within the slums, it may be possible to identify when it is prevalent throughout the year. Using this method, both spatial and temporal clusters may be identified and the seasonal effects on mental health could be observed. As such, information regarding such factors as seasonal climate, air pollution, living conditions, labour availability, and religious aspects (Ramadan) could be considered.

Our 2009 survey was accompanied by two other surveys that were subsequently conducted by Braun and Aßheuer (2011) and Zingel et al. (2011). They both focused on the effects of the socio-physical environment and connected the coping and adaptation strategies of the slum residents. Zingel et al. (2011) found that slums in Dhaka were by no means homogenous. The lack of income, in the context of dramatically rising food prices, was the most serious threat not only to food security, but also to health. Access to employment and income was particularly limited for female-headed households (i.e., the families of divorced or widowed women). It has been shown by other studies (Lund et al. 2010) that food insecurity has an impact on mental health. However, for the slum residents of Dhaka, this relationship has yet to be identified and, more importantly, the intensity of the impact of food insecurity on mental health is ambiguous to date. These relationships should be investigated while controlling for the individual and neighbourhood variables, as food insecurity implies stress and indicates vulnerability towards poor public health. Furthermore, a study by Braun and Aßheuer (2011) showed that slum dwellers in Dhaka could better cope with flood events when they had better social capital. Regardless of how strongly the people were affected, mutual help and support were the dominant features in times of crises. Our statistical neighbourhood definitions again may be compared to the findings of Braun and colleagues regarding local perceptions in the domain of flood coping behaviours.

Combining the survey data in a statistical model will enhance our understanding of the drivers of mental health in slums. Particularly, social capital is likely to play a major role in shaping mental health and this role has to be further investigated. This kind of study may provide more evidence that is needed to convince local decision makers.

Operating at the individual, household, and neighbourhood levels, this dissertation has introduced certain new insights regarding mental health in slums. However, drivers at the higher levels should also be investigated, such as land use, land cover dynamics and seasonal climatic variations. These kinds of studies require data of both broad scales and temporal resolutions. The LANDSAT or MODIS series of satellites and the DHS, as well as the Multiple Cluster Indicator Survey (MICS), may provide valuable data on a regularly basis. They are available for the whole country of Bangladesh (and beyond) but do not provide information on mental health. However, these data could be analysed with regard to other health outcomes in relation to urbanicity (i.e., typical urban features collected by remote sensing or survey data). As such, the processes that we documented with our in-depth analyses may be reproduced with a much larger set of samples.

4 Conclusions

One of the most pressing challenges of rapidly urbanising megacities in developing countries is the challenge of combating poverty. The urban poor are a vulnerable population group for whom mental health problems are common. With the three studies found in Chapters V, VI, and VII, additional evidence was presented regarding the determinants of mental health within Dhaka's slums. These specifically focused on the spatial inequalities of mental health both across and among the slums and population groups, which could provide evidence for neighbourhood associations with mental health.

The WHO-5 scores were positively correlated with other health outcomes such as "self-rated health" and negatively correlated with "having had a disease." This was interpreted to support the hypothesis that the WHO-5 Well-being Index is a measure that can be quickly and easily used to assess mental health in slums, as well as being less costly than other existing mental health measures.

The most important factors that determined mental health were job satisfaction, income generation ability, population density, flood non-affectedness, sanitation, quality, sufficiency and durability of the house, and selected properties of the natural environment. Individual-level characteristics such as diseases, gender, and health knowledge were important mental health determinants. Adding to the existing literature on public health in slums, this thesis provides empirical evidence for the local variation of well-being in the selected slums of Dhaka. Regarding the neighbourhood based on the three nearest (sampled) neighbours, the residents within the identified clusters were significantly more similar to each other in terms of well-being than they were to other slum residents. Furthermore, the clusters showed that similar socio-physical characteristics of neighbourhoods were related to their respective mental health status.

However, spatial dependencies are sensitive to spatial relationships (i.e., the definition of the neighbourhood under investigation). As a result, knowledge of the spatial distribution and structure of one's health status may provide knowledge regarding a community's social fabric and its related determinants of mental health. One's residence determines mental health independent of the individual/household factors. Slum settlements were shown to comprise various neighbourhoods with different socio-physical features. These neighbourhood features and their associations with mental health were confirmed in this thesis.

This methodology helps to avoid the violation of data independence that affects many statistical approaches. Spatial epidemiological models could thus lead to improved rationales for public health interventions and might strengthen policy significance, as they enable a more efficient and effective spatial allocation of scarce resources to target poverty alleviation and improve living standards in Dhaka and in comparable settings worldwide. A more widespread use of spatial epidemiological approaches is warranted in similar public health studies, as these conclusions may be relevant for slums of developing countries. Having provided evidence for the importance of the problem, this thesis concludes the crucial need to further concentrate on the Millennium Development Goals (MDGs) with the incorporation of mental health issues, especially in developing countries.

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Appendix A:
The WHO (five) Well-being Index (1998 version)

Psychiatric Research Unit
WHO Collaborating Centre in Mental Health

WHO (Five) Well-Being Index (1998 version)

Please indicate for each of the five statements which is closest to how you have been feeling over the last two weeks. Notice that higher numbers mean better well-being.

Example: If you have felt cheerful and in good spirits more than half of the time during the last two weeks, put a tick in the box with the number 3 in the upper right corner.

	Over the last two weeks	All of the time	Most of the time	More than half of the time	Less than half of the time	Some of the time	At no time
1	**I have felt cheerful and in good spirits**	5	4	3	2	1	0
2	**I have felt calm and relaxed**	5	4	3	2	1	0
3	**I have felt active and vigorous**	5	4	3	2	1	0
4	**I woke up feeling fresh and re-sted**	5	4	3	2	1	0
5	**My daily life has been filled with things that interest me**	5	4	3	2	1	0

Scoring:

The raw score is calculated by totalling the figures of the five answers. The raw score ranges from 0 to 25, 0 representing worst possible and 25 representing best possible quality of life.

To obtain a percentage score ranging from 0 to 100, the raw score is multiplied by 4. A percentage score of 0 represents worst possible, whereas a score of 100 represents best possible quality of life.

Figure A-1: The WHO (Five) Well-Being Index. Source: (WHO 2010)

Interpretation:

It is recommended to administer the Major Depression (ICD-10) Inventory if the raw score is below 13 or if the patient has answered 0 to 1 to any of the five items. A score below 13 indicates poor wellbeing and is an indication for testing for depression under ICD-10.

Monitoring change:

In order to monitor possible changes in wellbeing, the percentage score is used. A 10% difference indicates a significant change (ref. John Ware, 1995).

Figure A-1 (continued): The WHO (Five) Well-Being Index. Source: (WHO 2010)

Appendix B:
Supplementary material for Chapter VI - Local cluster maps

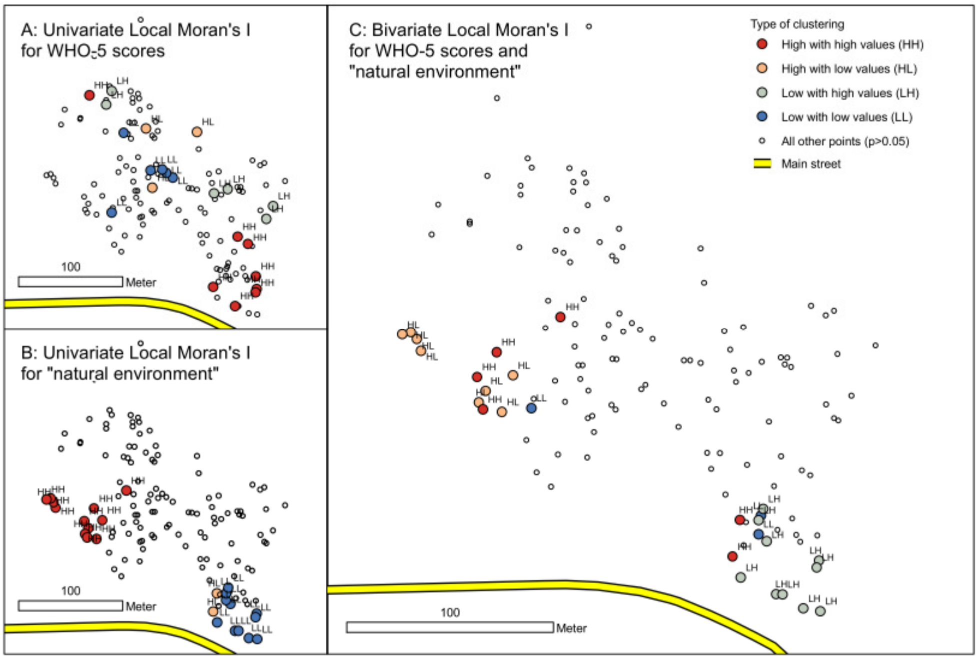

Figure B-1: Mental health (WHO-5 scores) and "natural environment" of males in the slum settlement Bishil/Sarag. Each dot on the map indicates a slum household (GPS point). The maps indicate significant (p<0.05) spatial clusters of high (HH) or low (LL) WHO-5 scores (A), "natural environment" (B), or similar values of both WHO-5 scores and "natural environment" (C), respectively. High values surrounded by low values (HL) and vice versa (LH) indicate outliers. The three nearest neighbours of a household were used in the statistics.

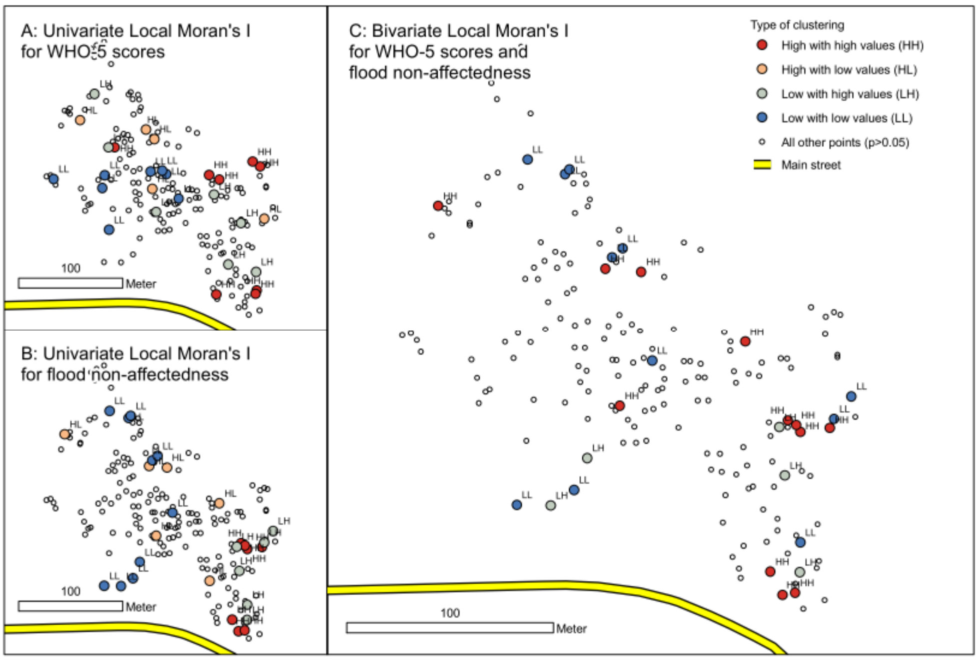

Figure B-2: Mental health (WHO-5 scores) and flood non-affectedness of young adults in the slum settlement Bishil/Sarag. Each dot on the map indicates a slum household (GPS point). The maps indicate significant (p<0.05) spatial clusters of high (HH) or low (LL) WHO-5 scores (A), flood non-affectedness (B), or similar values of both WHO-5 scores and flood non-affectedness (C), respectively. High values surrounded by low values (HL) and vice versa (LH) indicate outliers. The three nearest neighbours of a household were used in the statistics.

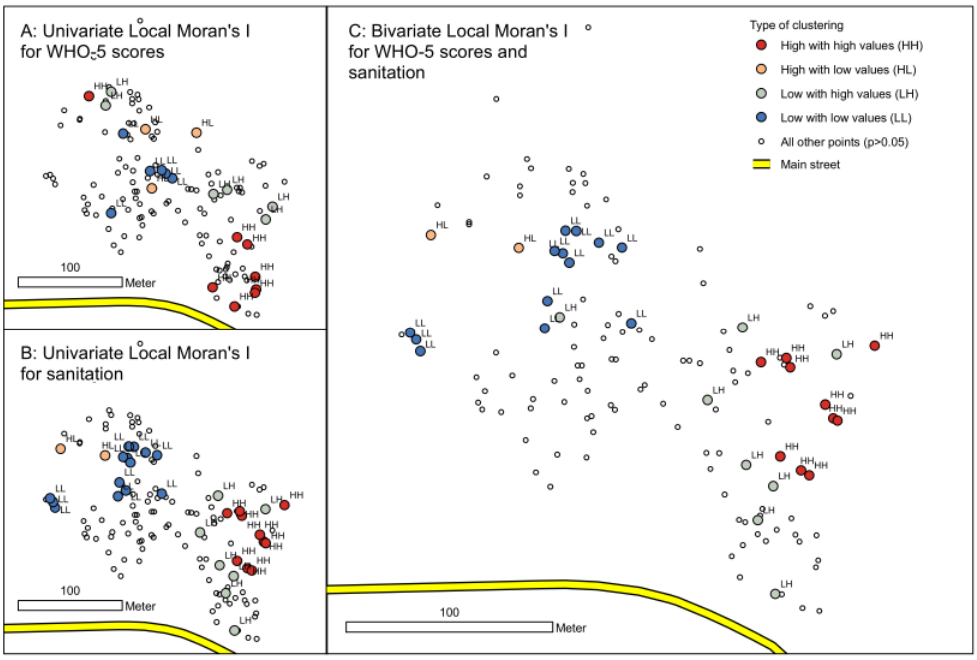

Figure B-3: Mental health (WHO-5 scores) and sanitation of males in the slum settlement Bishil/Sarag. Each dot on the map indicates a slum household (GPS point). The maps indicate significant ($p<0.05$) spatial clusters of high (HH) or low (LL) WHO-5 scores (A), sanitation (B), or similar values of both WHO-5 scores and sanitation (C), respectively. High values surrounded by low values (HL) and vice versa (LH) indicate outliers. The three nearest neighbours of a household were used in the statistics.

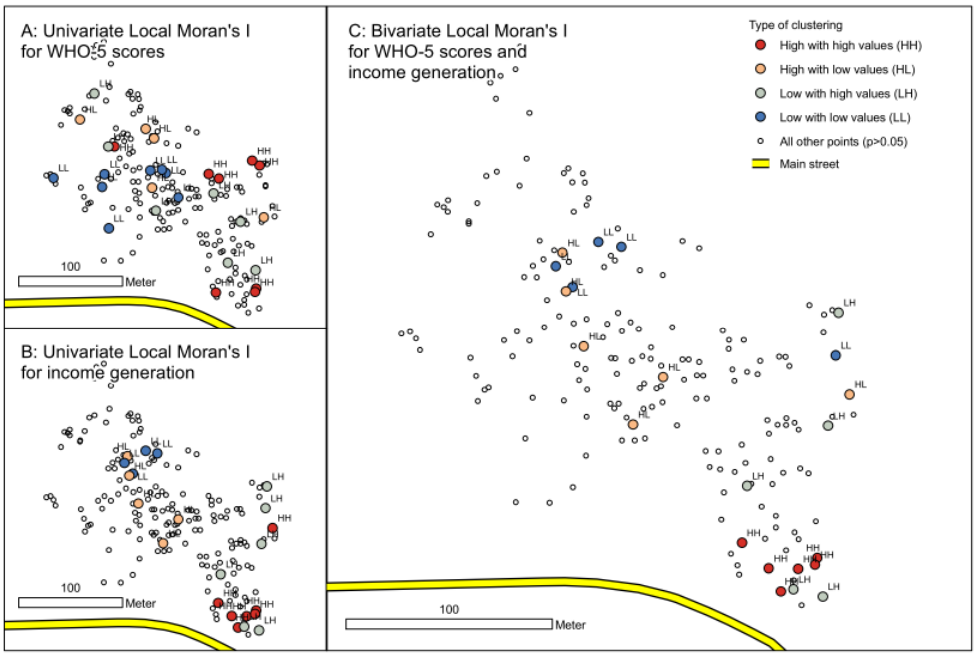

Figure B-4: Mental health (WHO-5 scores) and income generation of young adults in the slum settlement Bishil/Sarag. Each dot on the map indicates a slum household (GPS point). The maps indicate significant ($p<0.05$) spatial clusters of high (HH) or low (LL) WHO-5 scores (A), income generation (B), or similar values of both WHO-5 scores and income generation (C), respectively. High values surrounded by low values (HL) and vice versa (LH) indicate outliers. The three nearest neighbours of a household were used in the statistics.

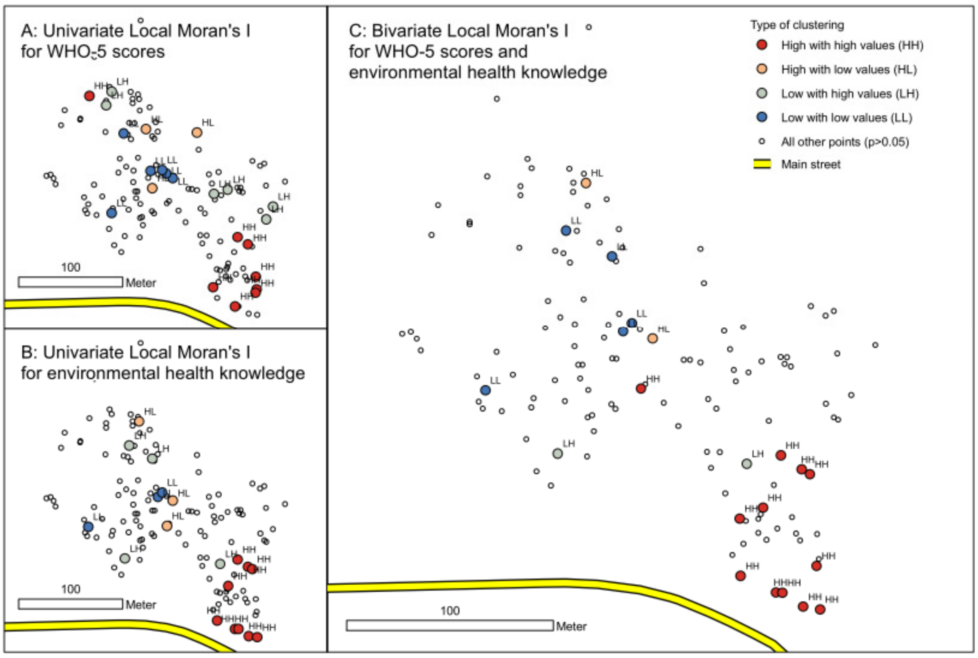

Figure B-5: Mental health (WHO-5 scores) and environmental health knowledge of males in the slum settlement Bishil/Sarag. Each dot on the map indicates a slum household (GPS point). The maps indicate significant ($p<0.05$) spatial clusters of high (HH) or low (LL) WHO-5 scores (A), environmental health knowledge (B), or similar values of both WHO-5 scores and environmental health knowledge (C), respectively. High values surrounded by low values (HL) and vice versa (LH) indicate outliers. The three nearest neighbours of a household were used in the statistics.

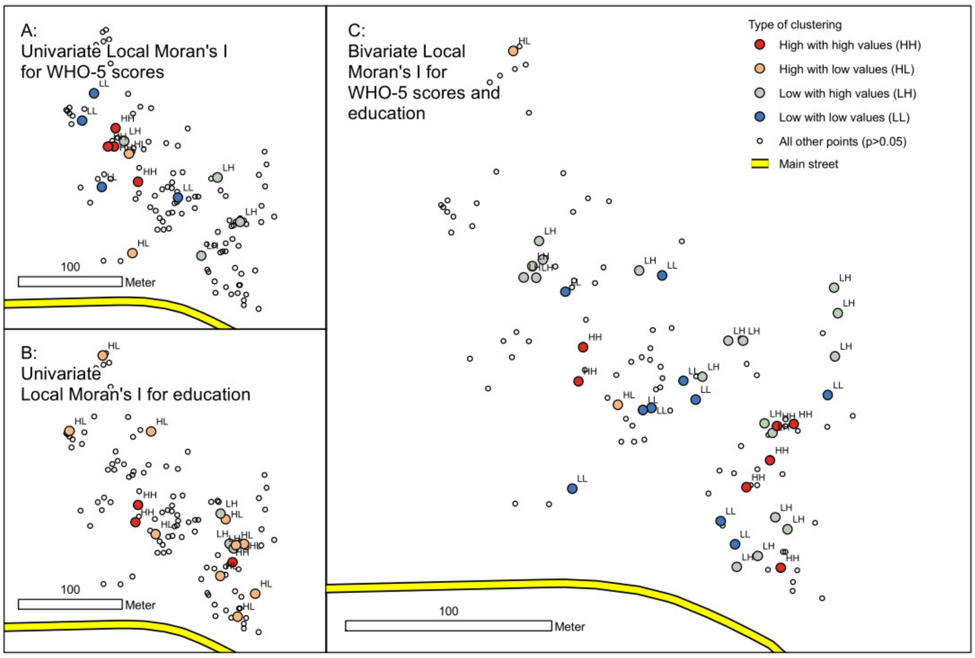

Figure B-6: Mental health (WHO-5 scores) and education of females in the slum settlement Bishil/Sarag. Each dot on the map indicates a slum household (GPS point). The maps indicate significant ($p<0.05$) spatial clusters of high (HH) or low (LL) WHO-5 scores (A), education (B), or similar values of both WHO-5 scores and education (C), respectively. High values surrounded by low values (HL) and vice versa (LH) indicate outliers. The three nearest neighbours of a household were used in the statistics.

Eidesstattliche Erklärung

Hiermit erkläre ich, die vorliegende Dissertation selbstständig und ohne Verwendung unerlaubter Hilfe angefertigt zu haben. Die aus fremden Quellen direkt oder indirekt übernommenen Inhalte sind als solche kenntlich gemacht. Die Dissertation wird erstmalig und nur an der Humboldt-Universität zu Berlin eingereicht. Weiterhin erkläre ich, nicht bereits einen Doktortitel im Fach Geographie zu besitzen. Die dem Verfahren zu Grunde liegende Promotionsordnung ist mir bekannt.

Oliver Grübner

Berlin, 10. August 2011